

**ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES**

PhD THESIS

Abidin ÇALIŞKAN

IMAGE DENOISING IN VOLUME RENDERING

**DEPARTMENT OF ELECTRICAL AND ELECTRONICS
ENGINEERING**

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Doctor of Philosophy by the board of jury on 19/06/2018.

.....
Prof. Dr. Ulus ÇEVİK
SUPERVISOR

.....
Prof. Dr. Abdullah ÇAVUŞOĞLU
MEMBER

.....
Assoc. Prof. Dr. Esen YILDIRIM
MEMBER

.....
Assoc. Prof. Dr. Turgay İBRİKÇİ
MEMBER

.....
Assoc. Prof. Dr. Mustafa ORAL
MEMBER

This PhD Thesis is written at the Department of Institute of Natural and Applied Sciences of Çukurova University.

Registration Number:

**Prof. Dr. Mustafa GÖK
Director
Institute of Natural and Applied Sciences**

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ABSTRACT

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IMAGE DENOISING IN VOLUME RENDERING

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: Assoc. Prof. Dr. Esen YILDIRIM
: Assoc. Prof. Dr. Turgay İBRİKÇİ
: Assoc. Prof. Dr. Mustafa ORAL

In this study, output images produced by medical imaging systems, which have an important role in the diagnosis and treatment of the disease, are used. If the noises of the images used in the medical field are not sufficiently reduced, the use of these images as a medical purpose and diagnosis of the disease becomes very difficult. For this purpose, a new machine learning approach, Extreme Learning Machines (ELM), has been applied for determining noisy pixels in medical images and denoising. The reason behind selecting this method is not only for denoising pixels, but also maintaining critical structural information that can be used for disease diagnosis. The classification techniques (ANN and SVM) with filtering methods (Gauss, NLMF and Kuwahara) are compared with our study. After filtering, some commonly used statistical parameters (MSE, PSNR and SSIM) are calculated to measure the similarity between filtered and original images. The effect of the ELM method on medical images was compared by using multiple computerized tomography (CT) images. The results showed that this method is statistically effective and produces more accurate and higher success rates than other methods.

Key Words: Medical imaging, noise detection, extreme learning machines, denoising, filtering

ÖZ

DOKTORA TEZİ

HACİM İŞLEMEDE GÜRÜLTÜ TEMİZLEME

Abidin ÇALIŞKAN

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: Doç. Dr. Turgay İBRİKÇİ
: Doç. Dr. Mustafa ORAL

Bu çalışmada, hastalığın tanı ve tedavisinde önemli bir yere sahip olan tıbbi görüntüleme sistemlerinin ürettikleri çıktıların görüntüleri kullanılmıştır. Medikal alanda kullanılan görüntülerin gürültüleri yeterince azaltılmaz ise bu görüntülerin tıbbi amaç olarak kullanılması ve hastalığın teşhisi çok zor hale gelir. Bu amaçla da, tıbbi görüntülerdeki gürültülü pikselleri tespit etmek ve gürültüleri temizleme için yeni bir kaynak ayrıştırma yöntemi olan aşırı öğrenme makineleri (ELM) metodu uygulanmıştır. Bu yöntemin seçilmesinin sebebi sadece gürültülü pikselleri temizlemek değil, aynı zamanda hastalık teşhisi için kullanılabilecek kritik yapısal bilgileri korumaktır. Yapılmış çalışma ile yaygın olarak kullanılan sınıflandırma tekniklerinden ileri beslemeli yapay sinir ağları (YSA) ve destek vektör makineleri (SVM) ile filtreleme yöntemlerinden Gauss, NLMF ve Kuwahara filtreleri ile karşılaştırılmıştır. Filtreleme işleminden sonra, filtrelenmiş ile orijinal görüntüler arasındaki benzerliğin ölçülmesi için yaygın olarak kullanılan bazı istatistiksel parametreler (MSE, PSNR ve SSIM) hesaplanmıştır. Çok sayıda bilgisayarlı tomografi (CT) görüntüsü kullanılarak, ELM yönteminin tıbbi görüntüler üzerindeki etkisi kıyaslanmıştır. Bu yöntemin istatistiksel olarak etkili olduğu, diğer yöntemlerden daha doğru ve yüksek başarı oranları ürettiği raporlanmıştır.

Anahtar Kelimeler: Tıbbi görüntüleme, gürültü tespiti, aşırı öğrenme makineleri, gürültü temizleme, filtreleme

GENİŞLETİLMİŞ ÖZET

Bilgisayar teknolojilerindeki gelişmeler, medikal görüntüler yardımıyla anatomik yapılar hakkında daha fazla bilgi edinilmesine imkân tanımaktadır. Günümüzde elde edilen iki boyutlu (two dimensional – 2D) medikal görüntü kesitleri işlenerek, üç boyutlu (three dimensional – 3D) anlamlı görüntülerin oluşması sağlanmaktadır. Bu işlenmiş veriler ise medikal alanlarda teşhis ve tedavileri kolaylaştırmaktadır. Medikal olarak elde edilen görüntüler kullanılmadan önce onarıma tabi tutulurlar. Özellikle bilgisayarlı tomografi (computed tomography – CT) ve manyetik rezonans (magnetic resonance – MR) görüntü kesitleri üzerinde uygulanan yöntemler bu görüntülerden olabildiğince faydalanılmasına imkân sağlamaktadır. Tıbbi görüntülerin elde edilme sürecinde kontrast, parlaklık ayarlamaları gibi çevresel faktörler veya görüntülerde var olan yapay nesnelerden dolayı bazı gürültüler meydana gelebilmektedir. Medikal alanda kullanılan görüntülerin gürültüleri yeterince azaltılmaz ise bu görüntülerin tıbbi amaçlarda kullanılması ve hastalıkların teşhisi çok zor hale gelmektedir.

Bu tezin temel amacı, son zamanlarda önemli bir yere sahip olan tıbbi görüntüleme sistemlerinin ürettikleri çıktılardaki gürültüleri etkin bir şekilde temizleyerek hastalığın tanı ve tedavisini kolaylaştırmaktır. Bu çalışmada, farklı konumlardan alınmış olan 2D gürültülü CT kadavra kesitleri kullanılmış olup, gürültülü pikselleri tespit etmek ve gürültüleri temizleme amacıyla başarılı ve yeni bir gizli kaynak ayrıştırma yöntemi olan aşırı öğrenme makineleri (extreme learning machine – ELM) yöntemi kullanılmıştır. Yapay öğrenme yöntemlerinden olan ELM yöntemi, hızlı çalışan ve efektif sonuçlar üreten geri yayılım tabanlı yapay sinir ağları yönteminin dezavantajlarını ortadan kaldırmak için önerilmiştir. ELM, gizli katman ağırlıklarının ayarlanmasına ihtiyaç duymamaktadır. Giriş ağırlıklarının eğitim verisinden bağımsız olarak rassal yöntemlerle ataması yapılarak gizli katman ağırlık değerleri analitik yöntemlerle hesaplanır. Bu yöntem, oluşturduğu sinir ağının giriş ağırlıkları ile gizli düğüm eğimi değerlerini rassal olarak oluşturmakta ve çıktı katman ağırlıkları en küçük kareler yöntemi ile hesaplamaktadır. Bu yöntem, eğitim

hatası ve çıkış ağırlıklarının normlarını minimize ederek ikili sınıflama, çoklu sınıflama ve regresyon problemleri için yüksek genelleştirilmiş performans sunmaktadır.

CT imgelerindeki gürültülü pikseller ELM yöntemi ile tespit edilerek sınıflandırılmıştır. Sınıflandırma aşamasında her bir görüntü için komşuluk pikselleri dikkate alınmıştır. Gürültülü piksellerin koordinatlarına bakılarak kendi çevrelerindeki piksel değerleri ile bir önceki ve bir sonraki imgenin piksel değerlerine bakılmıştır. Her bir gürültülü piksel değeri, veri setindeki diğer pikseller ile karşılaştırılarak sadece gürültüsüz olan piksellerin ortalamasının alınması ile yeni piksel değeri ile değiştirilmiştir. CT imgeler gürültüden temizlendikten sonra 3D yüzey model oluşturularak, modelin histogramı çıkarılmıştır. Gürültülü olan piksel değerlerinden elde edilmiş olan histogram ile gürültülü pikseller temizlendikten sonraki histogram karşılaştırılmıştır. Yeni piksel değerlerinin dağılımının başarılı bir şekilde normalize edildiği ve normal bir dağılım gösterdiği gözlemlenmiştir.

Gürültüye maruz kalan görüntülerin filtrelenmesinden sonra orijinal görüntüye ne kadar benzediğinin ölçülmesi performans kriterleri ile hesaplanmıştır. Performans kriterleri, ortalama karesel hata (mean square error – MSE), tepe sinyal gürültü oranı (peak signal to noise ratio – PSNR) ve yapısal benzerlik indeksi (structural similarity index – SSIM) ile hesaplanmıştır. Bu kriterler ile farklı yöntemlerin aynı görüntü üzerindeki etkileri sistematik bir şekilde karşılaştırılarak hangi yöntemin daha başarılı olduğu tespit edilmiştir.

ELM sınıflandırma sisteminin gizli katmandaki nöron sayısı arttıkça başarı oranının arttığı ancak, sistem doyuma ulaştıktan sonra nöron sayısındaki artışın başarı oranını değiştirmediği görülmüştür. Sınıflandırma sisteminin doyuma ulaşması (overfitting) durumunda algoritma esas problemi çözmekten uzaklaşır ve kendisine verilen değerleri tutturmaya odaklanır. Bu durumdan dolayı algoritma asıl çözmesi gereken problemi çözmekten uzaklaşır. Nöron sayısının belirli bir orandan sonra artırılması sisteme ek bir yük olacağından nöron sayısının optimum düzeyde tutulması gerekmektedir. Gizli katmandaki nöron sayısının 250 olduğu katmanda

doyma ulaşıldığı gözlemlenmiştir. En yüksek başarı oranları, ELM 87.20, MSE 0.148, PSNR değeri de 56.46 olarak elde edilmiştir. Her bir imgenin komşuluğu olan imgelere bakılarak, gürültülü olan piksel değerlerinden elde edilmiş olan SSIM değerleri ile gürültülü pikseller temizlendikten sonra ki SSIM değerleri karşılaştırılmıştır. Veri setindeki komşu imgelerin ortalama SSIM değeri gürültülü olan orijinal imgelerde 0.896, temizlenmiş olan imgeler ise 0.946 değerine ulaştığı görülmüştür. Sonuçlara bakıldığında, SSIM değerinin artış gösterip bir değerine yaklaştığı görülmüştür.

Yapılmış çalışma ile yaygın olarak kullanılan sınıflandırma teknikleri olan çok katmanlı ileri beslemeli yapay sinir ağları (multi-layer feed-forward neural network – MLP-FNN), destek vektör makineleri (support vector machines – SVM) ve Gauss, yerel olmayan ortalamalar (non-local means filter – NLMF) ve Kuwahara filtreleme yöntemleri karşılaştırılmıştır. Klasik istatistiksel yöntemler, regresyon aşamasında kısmen başarılı olabildikleri için son yıllardaki örneklerden öğrenme yapabilen, genelleme yeteneğine sahip ve istatistiksel yöntemlere göre daha az varsayımları olan makine öğrenmesi yöntemlerinden olan MLP-FNN ve SVM yöntemleri tercih edilmiştir. Karşılaştırma yöntemleri olarak kullanılmış olan Gauss, NLMF ve Kuwahara filtrelemeleri ise, görüntünün iyileştirilmesini sağlayan, gürültülerin çıkarılmasına katkıda bulunan ve nesne tanıma gibi farklı işlemler için kullanılan tekniklerdir.

ELM ile karşılaştırılan MLP-FNN ve SVM sınıflandırma yöntemlerinin sigmoid çekirdek fonksiyonunu kullanarak k-katlamalı çapraz doğrulama tekniği ile $k=5$ değeri için performansları hesaplanmıştır. Verilerin %80'ni eğitim ve %20'si test kümesi olarak ele alınmıştır. Karşılaştırılan yöntemlerin başarı oranları ise SVM % 83.35, MLP-FNN % 82.17, Gauss % 77.73 Kuwahara % 79.17 ve NLMF % 72.92 olduğu görülmüştür.

Kullanılmış olan kadavranın kafa bölümünün CT kesit gürültülerini görmek için ilk olarak, veri tabanındaki bütün imgelerden hacim işleme teknikleri ile 3D yüzey model oluşturulmuştur. Gürültülü olan 3D yüzey modelin histogramı çıkarılarak veri tabanı içerisindeki tüm imgelere ait piksel değerlerinin yoğunluk

değerleri bulunmuştur. 3D modelin histogramında gürültülerden kaynaklı olarak piksellerin yoğunluk değerlerinin normal bir dağılım göstermediği görülmüştür. CT imgeler gürültüden temizlendikten sonra 3D yüzey model tekrar oluşturularak modelin histogramı çıkarılmıştır. Gürültülü olan piksel değerlerinden elde edilmiş olan histogram ile gürültülü pikseller temizlendikten sonraki histogram karşılaştırıldığında, yeni piksel değerlerinin dağılımının başarılı bir şekilde normalize edildiği ve normal bir dağılım gösterdiği gözlemlenmiştir.

Çok sayıda CT kesiti kullanılarak, ELM yönteminin tıbbi görüntüler üzerindeki etkisi kıyaslanmıştır. Sınıflandırma sistemlerinin sonuçları, filtreleme yöntemlerinin performansları ile birlikte elde edilen MSE, PSNR ve SSIM gibi yaygın olarak kullanılan bazı istatistiksel ölçümler hesaplanıp karşılaştırmalar yapılmıştır. Bu yöntemin istatistiksel olarak etkili olduğu, diğer yöntemlerden daha doğru ve yüksek başarı oranları ürettiği raporlanmıştır.

Önerilmiş olan ELM yönteminin gürültülü görüntüler üzerindeki etkisi diğer sınıflandırma ve filtreleme yöntemlerine göre kıyaslanmış olup ELM'nin daha doğru ve yüksek başarı oranları ürettiği görülmüştür. MLP-FNN ve SVM sınıflandırma performans değerlerinin düşük olduğu ve Gauss, NLMF ve Kuwahara filtrelerinin gürültülü olan pikselleri temizlemeye çalışırken gürültüsüz bölgelerdeki piksel değerlerini değiştirdikleri gözlemlenmiştir. Filtreler gürültülü pikselleri tespit etmiş ancak bunun yanında gürültüsüz piksel değerlerini de tespit ettikleri görülmüştür. Tıbbi görüntülerde, gürültülü piksellerin temizlenmesi aşamasında gerçek piksel değerlerinin değişmemesi gerekmektedir. Tıbbi alanda kullanılan imgelerdeki her bir piksel tanı ve tedavi sürecinde ayrı bir öneme sahiptir.

ELM yöntemi diğer yöntemler ile karşılaştırıldığında gürültülü piksellerin tespit edilmesi ve gürültülü olan her bir pikselin yerine gelecek olan piksel değerinin tahmin edilmesinde başarılı sonuçlar göstermiştir. Sonuçlar ELM yönteminin gürültülü piksel tahmininde ve gürültüleri temizlemede kullanılabileceğini göstermiştir. Deney sonuçları, önerilen yöntemin istatistiksel olarak verimli olduğunu, daha doğru ve yüksek performans sonuçları verdiğini göstermiştir.

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LIST OF ABBREVIATIONS

1D	: One-Dimensional
2D	: Two-Dimensional
3D	: Three-Dimensional
ANN	: Artificial Neural Network
CC	: Cartesian Cubic
CG	: Computer Graphics
CNN	: Convolutional Neural Network
CT	: Computed Tomography
DB	: Decibel
ELM	: Extreme Learning Machines
MLP-FNN	: Multi-Layer Feed-Forward Neural Networks
GPU	: Graphics Processing Unit
HU	: Hounsfield Unit
MIP	: Maximum Intensity Prediction
MR	: Magnetic Resonance
MSE	: Mean Square Error
NLM	: Non-Local Means
NLMF	: Non-Local Means Filter
PDE	: Partial Differential Equations
PSNLM	: Pre-smoothing Non Local Means
PSNR	: Peak Signal to Noise Ratio
RC	: Ray Casting
RT	: Ray Tracing
SLFN	: Single Hidden Layer Feed-Forward Neural Networks
SSIM	: Structural Similarity Index
SW	: Search Window
US	: Ultrasound
VD	: Volume Data
VG	: Volume Graphics
VR	: Volume Rendering
VV	: Volume Visualization



1. INTRODUCTION

Biomedical devices in many health units, from small clinics to large hospitals, have an important place in the diagnostic and therapeutic stages of medical science. The digital images taken from these devices have important usage areas in many applications of daily life. The use of images obtained from many methods such as computed tomography (CT), magnetic resonance (MR) imaging and ultrasound (US) is very common, especially in the diagnosis and treatment of medical field conditions.

It was observed that the data obtained from CT and MR devices in the foreground was made up of images taken in different positions such as head, and femur in certain areas (Drzezga et al., 2012; Hitz et al., 2014). Parasitism or problems arising from the environment are some of the various problems (James et al., 2014; Ritter et al., 2011). In order to provide the desired standards in the images, the problems can be overcome by using image processing techniques (Rowe and Fishman, 2017).

There are a lot of imaging techniques for different applications to observe and monitor the anatomical and physiological conditions of the patient (Bansal et al., 2014). These methods introduce noise and artifacts during medical image processing (Boas and Fleischmann, 2012; Mohan et al., 2014). So far, there have been a lot of studies conducted on denoising (Bahendwar and Sinha, 2015; Bansal et al., 2014; Klosowski and Frahm, 2017; Mohan et al., 2014; Naimi et al., 2015) and segmentation (Baumgartner et al., 2017; Pratondo et al., 2017; Taha and Hanbury, 2015) the images in medical field. If the image consists of noise or various objects having complex figures, it becomes difficult to determine the edges automatically (Kermad and Chehdi, 2002). Furthermore, in various applications like biomedical images; the object in the image is interested. In such cases, user-interactive semi-automatic image segmentation techniques are recommended (Zhang et al., 2005). In interactive segmentation techniques, user can select a point within the region with

similar properties and then the points providing the edge criteria could be automatically determined by moving away from this point (Liu and Ma, 1999; Qiu and Mukherjee, 2011; Urban and Tester, 2009). However, the current methods try to segment the image by considering the area growing from the selected point.

In recent years, there has been a rapid increase in the number of studies on noise reduction methods in medical field. This is also due to the increase in the amount of noise caused by low-dose CT and MR imaging devices on the image. So far, many denoising methods have been proposed to improve image quality by removing noise in digital images and to protect important information in the image. These methods including Gaussian filter (Jain and Tyagi, 2016), linear filter (Verma and Ali, 2013), non-local means filter (NLMF) (Li and Suen, 2016), kuwahara filter (Djurović, 2017), anisotropic diffusion, bilateral and trilateral filters (2016), non-linear filters such as median filters (Zhang et al., 2016), wavelet thresholding (Naimi et al., 2015), neighboring filters (Riji et al., 2015), modification based on the minimization of the total variation on the image (Shen et al., 2017) and methods based on the soft wavelet threshold (Pan et al., 2016) can be given as examples.

Methods and techniques giving more precise results in imaging processing according to euclidean geometry by using Fractal geometry and providing to obtain more precise results by establishing similarity foundations of the image have been started to be used in recent years (Liu et al., 2014; Milošević et al., 2017). Segmentation and fractal analysis method used in studies where the processes analysis are performed (Fang et al., 2017; Akar et al., 2017). In addition, a number of criteria is used to determine the success of such methods. These are mean square error (MSE), peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) calculations.

In this study, 2D/3D denoising techniques with surface, and volume rendering (VR) techniques, which used in the creation of 3D surface model were investigated. 3D surface model was also created to see the noises in the CT images of the head part of the cadaver. Then, the ELM method has been applied to detect

the noises in all CT images in the database. Moreover, the performances of different filtering methods were compared to each other by using some statistical metrics such as MSE, PSNR and SSIM, which are obtained together with the results of the classifier system.

1.1. Purpose and Contributions of the Thesis

In this section, an overview of purpose and contributions of the thesis are presented. The main purpose of this thesis is to accurately detect the noises and denoising in the medical images being used to diagnose the disease.

Denoising 2D medical image data is difficult because many factors have negative impacts during capturing image data from medical devices. These impacts are usually environmental effects such as contrast and brightness adjustments, and removal of the artificial figures from the whole or a part of the image. Denoising CT or MR images are substantially important for analysis of the disease. If the noise and artifacts are not sufficiently minimized, the diagnosis becomes more difficult. Many filtering methods exist for denoising. Sometimes, the artifacts can be an adverse effect. The noises should be removed in order to get a clear image.

In this study, noisy CT cadaver images taken from different positions were used. It is aimed to correctly determine and classify the noisy pixels of CT images by using ELM classification method. In the following process, the deviations from the real pixel values of the noisy pixels are estimated and the new pixel values are calculated by considering the neighborhood relations.

The ELM method has been proposed to remove the disadvantages of the backpropagation based ANN method, which produces fast acting and effective results. The ELM randomly generates the input node weights and the hidden node pitch values of the neural network and calculates the output layer weights using the least squares method. In the ELM method, high generalized performance is provided for binary classification, multiple classification and regression problems by minimizing the norm of training errors and output weights. The ELM is performed

with a regulated MSE and can be extended with the application of kernel methods. The Least squares method is also a standard regression method used to write the mathematical connection between two physical quantities that change in relation to each other as real as possible. In other words, this method serves to find a function curve that will go as close as possible to the data points obtained as the result of the measurement.

The effect of the proposed ELM method has also been compared with classification techniques of multi-layer feed-forward neural networks (MLP-FNN) and support vector machines (SVM) and also filtering methods of Gauss, Kuwahara and NLMF. Moreover, the performances were compared to each other by using some statistical metrics such as MSE, PSNR and SSIM, which are obtained together with the results of the classifier system. Since classical statistical methods can be partially successful at the regression stage, machine learning methods of MLP-FNN and SVM which are capable of learning, having generalization ability and fewer assumptions than statistical methods, have been preferred. According to the results obtained, it was reported that ELM produced more accurate and high success rates. As a result, comparing to the other methods, the ELM method has been successful in detecting noisy pixels and also successful results have been obtained by estimating the pixel value that will be replaced by each noisy pixel. The results show that the ELM method can be used to estimate noisy pixels and to denoising.

1.2. Literature Review

Owing to the advancement of technology, the images are transferred to a digital environment (Urban et al., 2009). In order to qualify an image as a digital image, a device that makes digital image recording should obtain it. Image processing is the science of making purposive changes on the images (Rowe and Fishman, 2017). It is used to correct the defects and errors in the information that is transformed into a digital image. Image processing, which takes place in numerous

application areas by using various techniques, involves a wide area (Çalışkan and Çevik, 2016).

Medical imaging systems are among leading areas where image processing is used at most. It is a very important part of healthcare for diagnosis of diseases. It is a field that has been attracting attention rapidly in recent years, and researchers have been gathering momentum (Göröcs and Ozcan, 2013; Vroomen et al., 2017; Pfeiffer et al., 2013; Tanter and Fink, 2014). It is also a source of inspiration for many study fields and problems in terms of the devices used and the processing of the digital images obtained from these devices.

Although the devices are in the foreground in the biomedical field, it is of great significance how the images obtained from these devices are processed, how they are structured and how they are made consistent with each other (Dou et al., 2016; Singh et al., 2015).

Despite the fact that the devices give very sensitive data in a period of time, medical images have become so important. It is not possible to prevent certain parasitism and spots at some areas in the images to some extent due to factors such as radiation, light coming into the environment and human (Jiang et al., 2010; Mingliang et al., 2016; Torbati et al., 2014). The elimination of these impurities in the images and the requests emerging over time, taking the images from 2D to 3D, specifying the contours, the desire to draw the contours and realizing product designs from these data are required processing of medical images. There are several studies in this area. The first algorithm was to the linear filters (Ram et al., 2013), the convolutions with the low-pass filtering function, the filtering over the frequency range, the Wiener filter (Storozhilova et al., 2012). The linear process inevitably suffers from quality degradation such as disadvantages, loss of sharpness, edge blur and knife effects. Kim and Yaroslavsky (1986) have introduced many of the image filtering methods, which are called as rank algorithms. The Median filter is a well-known method among these, providing fast computational algorithms (Huang et al., 1979; Weiss, 2006; Perreault and Hebert, 2007). This method preserves the sharp

edges of the image but rounds the corners. Basic principle of edge searching operators is based on the comparison of the brightness values between the neighbors of every pixel in the image (Lee and Chung, 2005; Urban et al., 2009; Zhu et al., 2010).

Recent works highlight the advantages of a way in which the average pixel depends on the statistics in the neighborhood as well as the value of the pixel (Bansal et al., 2014; Buades et al., 2005; Dabov et al., 2007). In the NLM filter method, the average weight is calculated using similarity neighborhoods of the pixel. Many denoising algorithms have been proposed in which, the local statistics of the neighborhood in the filtering process is considered (Buades et al., 2010; Chatterjee and Milanfar, 2012; Lebrun et al., 2013). These algorithms compute the weighted average using sub-image statistics in order to predict the statistical measures over the pixel windows varying from 3x3 up to 15x15 (Loizou et al., 2005). Total variation minimization and regularization methods (Shen et al., 2017), nonlinear diffusion (Tschumperlé, 2006), local mode filters (Mrázek et al., 2006) are one of the methods of choice for eliminating noise (Kervrann and Boulanger, 2008). Most of these methods are based on a weighted average of gray pixel values in the spatial neighborhood (Elad, 2002). Zhang and Gunturk (2008) have proposed bilateral filters including spatial and intensive zones. The objective of all these methods is to remove the noise while keeping the information related to the image.

1.2.1. 2D Image Denoising

Majority of the image denoising methods in the literature are used for 2D images. An extended review of the 2D image denoising techniques has been given in this section.

Raj and Venkateswarlu (2012) have presented the denoising techniques for speckle reduction in ultrasound imaging. These techniques have been developed the noise reduction techniques employing multi scale transforms. Coupé et al. (2008) presented a new denoising method for a 2D image which firstly is proposed by

Buades et al. (2005). They suggest that the filter parameters be adjusted automatically to improve NLM filter. Moreover, they concentrated on mainly two scopes. The first one is defining a general methodology (mathematical and experimental) in order to compare and categorize noise reduction algorithms for classical images. Secondly, they proposed an algorithm based on NLM to preserve the structure of digital images. Comparing to the other methods, the NLM algorithm does not have the same assumptions related to the image. Alternatively, the method accepts that the image contains high self-similarity. Efros and Leung (1999) introduced the concept of self-similarity for texture synthesis. Majority of the denoising methods, in the literature, employs the linear filtering, which is based on point processing or weighted averaging of neighborhood gray levels. These methods, remove the noises for smoothing the edges, which is very important to diagnose the diseases from the images. Verma and Ali (2013) is a limited optimization of numerical algorithms to remove the noise of the image. Depending on the limit associated with noise statistics, the overall image change is minimized, and the Lagrange multipliers impose the limit. The artifact quality correction affects the performance. As a process, it is aimed to improve the quality of the image for better visualization. Especially for medical purposes, the preservation of the image is important. Noise reduction can be performed as part of the process or as a single process. Noise reduction is a component to improve image-processing algorithms (Verma and Ali, 2013).

Tschumperlé (2006) is used partial differential equations (PDE) for smoothing multi-valued images. A new constrained diffusion PDE which regularizes image data have been developed by Tschumperlé which considers image curvatures structure. This method is directly related with the continuous formulation of the Line Integral Convolutions, which provides high-speed design and stable algorithm. However, detecting such structures on noisy images is difficult work. On the other hand, when the diffusion is limited too much, it does not smooth the image edges sufficiently. While using trace based PDE, it is difficult to interchange between

complete noise removal and preserving the curved structures (Guillemot and Meur, 2014). Such regularization does not take smoothing of the curvature directions into account.

Jain and Tyagi (2016) reduced the normally distributed noise without blurring edges and used the theoretical foundation for local mode filtering. Meaning the filter can be easily extended to multi-channel image. Moreover, they proposed the Gaussian filter for the utilization of the local mode. Tomasi and Manduchi (1998) have introduced the bilateral filtering concept in order to preserve the edge for smoothing. It has been proven that the image color map is only distorted by range filtering. A simple non-iterative scheme has been proposed by them for edge preserving smoothing. Elad (2002) introduced a bridge showing the bilateral filter emerges from the Bayesian approach, which is a single iteration of the famous iterative algorithm. It is also illustrated that, the bilateral filter can be enhanced and extended for more general reconstruction problems.

In order to denoise the medical images, Deepa and Suganthi (2014) investigated that a contrast enhancement and denoising technique has been applied in their study. Where the medical image is given as an input and the image is denoised by using various filters. The quality and accuracy of the study are measured by MSE and PSNR values, and the filtered images are evaluated in accordance with the obtained values. Kumar and Diwakar (2016b) have proposed a wavelet transform based technique that preserves the edges while removing noise in the image. The method they propose mainly consists of two fundamental steps. In the first step, a CT image is threshold-based denoised with different window sizes. In the second step, a block-wise variation based wavelet domain operation is performed. Kalavathi and Priya (2016) have proposed a method known as histogram-based localized wiener filter to denoise MR brain images. They have provided a simple and useful method to relieve impulse noise in MR brain images. Methods were tested with brain images database. Bhadauria and Singh (2013) used an edge detection algorithm based on wavelet transform and canny operator. In the wavelet domain, the canny

operator detects low-frequency edges. They used PSNR method to evaluate the denoising success of the method. Gabralla et al. (2015) proposed a new denoising scheme using the soft-thresholding method and modifying the wavelet coefficients. They compared different wavelet denoising techniques for CT images. Chen et al. (2016) utilized multiple repetitive structures to denoise an image. Their study, focusing on finding similar structures in an image, is known as collaborative NLM filter. Yang et al. (2015) proposed a framework for pre-smoothing NLM (PSNLM) filtering with image transformation. They used the PSNLM frame for MR denoising with image transformation. Yang et al. (2017) designed a perceptive deep convolutional neural network (CNN) based on a perceptual loss as an objective function to denoise CT images. Jifara et al. (2017) modeled an effective deep feed forward CNN using a small training data set to denoise medical images. In addition, they used residual learning as a learning approach. Zhang et al. (2017) designed a denoising CNN to denoise images. They also used the residual learning method to separate noises from the images. Kumar and Diwakar (2016b) applied the haar-type wavelet transform technique to denoise CT images. They used tetralet coefficients, which have a high frequency that effectively protects the edges of the image while denoising the noise from the image. Chen et al. (2017) applied a new denoising method for low-dose CT with the deep learning method. They used a deep CNN method to remove low-dose CT images from the noise, and the method they use produces a feature mapping technique from low to normal dose images. Yang et al. (2017) developed a generative adversarial network technique for low-dose CT images.

The noise filtering that is used in 3D imaging is not efficient as 2D images (Çalışkan and Çevik, 2016). The 3D images are more complicated relative to 2D images. For example, determining the locations of the edges is more difficult in 3D images (Qiu and Mukherjee, 2011).

1.2.2. 3D Visualization and Denoising

In this section, the algorithms for a 3D surface model display by examining the techniques of CG, visualization, data types and their conversion to graphics components, imaging algorithms, surface and volume imaging techniques, segmentation, smoothing, 3D image denoising, image processing techniques such as shadowing, and complexity and efficiency properties of imaging algorithms were investigated.

In recent years, the 3D images have become more popular for image applications. The 3D images are used in various fields such as medical, animation and simulation (Fritscher et al., 2016; Onchis et al., 2017; Cleeren et al., 2014; Iwasa, 2015; Mooney et al., 2015; Rose et al., 2015). The existing 3D objects, the measurements of which are not known commonly or the models of which do not exist, can be remodeled. To do this, the reverse engineering technique should be used. The measurement data used in reverse engineering are obtained by using point clouds or cross-sections, coordinate measurement or optical, laser scanning devices (Galantucci et al., 2006; Jardini et al., 2014). Lai et al. (1999) used an algorithm, based on a reverse engineering technique, for 3D surface reverse construction of CT images. In the study conducted by Lai et al, an algorithm based on reverse engineering technique for 3D surface reconstruction of CT images has used. Firstly, the 2D contour of each CT section of the object was determined for pre-processing and then they formed the 3D surface model by applying a series of image analysis technique such as segmentation and edge detection.

In order to generate 3D computer assisted drafting model over the medical images, 3D models were tried to be formed with the help of contour algorithms (Ryu et al., 2004). The computer-focused algorithms presented by Lee and Chung (2005) in finding the contour specification and thresholding of the femur bone have shed light on such studies. Various software that uses volume or surface rendering techniques has been developed for 3D medical imaging techniques (Calhoun et al., 1999). Volume data (VD) obtained by medical imaging techniques such as MR and

CT have been used, and the "Marching Cubes" algorithm has been used for the 3D surface models of relevant areas (Lorensen and Cline, 1987). The "Marching Cubes" algorithm has been specified as the method that achieves the result in the fastest way in forming 3D data compared to the other algorithms and in terms of processing time and structure appropriateness (Guha, 1994; Chan and Purisima, 1997). By using a co-surface extraction method, the surface models have been obtained from the CT and MR data and, as a result of these applications, statistical data and results were achieved (Cignoni et al., 1996; Lee and Lee, 2006).

Liu and Ma developed a method providing 3D surface segmentation of contour data obtained from CT by benefiting from the seed-growing segmentation technique (Liu and Ma, 1999). After the pre-processes, they obtained layer-based 3D contour model in 2D CT images. There have been various studies conducted on denoising and segmentation from the images in medical imaging (Adams and Bischof, 1994; Shamir, 2008). Medical imaging has an effective role in 3D visualization, medical education and diagnosis of diseases without any requirement for surgical interventions. The simulations, particularly in the 3D models in the surgical field, have an important role for the developments in medical fields and in the diagnosis of the diseases without requiring surgical intervention (Malone et al., 2010; Rose et al., 2015). Especially the simulations in surgery are an important factor in the acceleration of medical developments. Generally, 3D images contain noise which should be cleaned before the improvement. The images that obtained with medical ways are repaired before using. Repair process involves the denoising within the image, contrast and brightness adjustment, and removal of the artificial figures of the whole image or a part of the image. These artificial figures or objects are the items that are placed in the body such as a stopping or prosthesis (Pizurica et al., 2006).

Liu and Ma (1999) used a layer-based core growth technique, and developed a method that provides the 3D segmentation of the contour data obtained from CT. They obtained the layer-based 3D contour model in 2D CT images after pre-

processes. Firstly, some segmentation processes were performed to eliminate the noises in the data. In addition to segmentation processes, filtering algorithms were tried to obtain the required contour areas. Additionally, studies were carried out in order to specify the thresholding values over the existing data.

In 3D CT images, the noise is close to white color due to reducing the dose of radiation on the patient. Storozhilova et al. (2012) carried out two different methods of reducing the noise of CT images, namely; 3D extension of fast rank and NLM algorithms. CT device provides to obtain images by taking the image sections, combining and transferring them in the computer environment (Prokop and Galanski, 2003). NLM is applied to 3D medical data by Coupé et al. (2013) using optimization of the original NLM. In this study, it has been proposed that the computational time can be substantially decreased by the voxel pre-selection and multithreading.

Romdhane et al. (2016a) applied a new method for 3D CT denoising based on the coherence enhancing diffusion model. In the applied model, the model inspires it (Pop et al., 2007). The denoising can be taken as a component of processing or as a process alone (Goyal et al., 2016). As a component, the denoising is used to improve the image processing algorithms (registration, segmentation).

Qiu and Mukherjee (2011) have proposed an original denoising procedure base on the nonparametric prediction of 3D jump surface from the noisy data. With this method, it is possible to preserve edges and major edge structures, e.g., intersections of two edge surfaces, pyramids, and pointed corners. Wong and Chung (2004) have proposed the trilateral filter, which is another original denoising method. With this method, the integration of geometric, photometric and local structural similarities is possible for filtering the medical images. 3D images can be simply filtered using this technique. Another 3D image denoising algorithm for segmentation using redundant discrete wavelet transform has been proposed by Vatsa et al. (2009). In this work, they used a two-stage algorithm for denoising with image fusion concept. Dabov et al. (2007) designed a new image denoising strategy

based on transform domains. They compared the experimental results, which has been obtained with the advanced algorithms. These algorithms are called as block-matching and 3D filtering.

1.3. Computer Graphics

In this section, CG and algorithms have been investigated. The computer has become a powerful tool for image processing. There is virtually no area where graphics displays cannot be used for any advantage (Çalışkan and Çevik, 2015). For that reason, it is not surprising to use the CG on such a wide scale (Khattak et al., 2012). While engineering applications are based on expensive equipment, advances in information technology made CG interactions a useful tool. CG has become an apart from graphics technology (Angel, 2013). Today, CG is often used in the fields of technology, art, entertainment, medicine, industry, business, government, advertising, education and other areas (Kaufman et al., 1993; Metaxas, 2012). CG has significant uses in the development process, especially for architectural and engineering systems and it is the art of rendering and displaying images on a computer screen. CG is one of the most exciting and strong-growing areas of current technology, and it is a standard function of applications and computer technology. CG systems are often used for most product development, training simulators, video products, music and television advertising, research, medical methods, data review, movies and many other operations (Liu et al., 2010). In particular, a large part of the current CG research is related to improving efficiency, reality, and visualization. Because of the wide recognition of the functionality and practicality of CG in almost all graphics areas, there are software and hardware systems. 2D and 3D application graphics are common in general aim computers, including a range of pocket computers (Marschner and Shirley, 2015). In 3D CG, the scene is geometrically patterned, usually with triangles; and the calculator is used to compute the way the scene is displayed at a particular angle from a particular perspective. One of the main objects of CG is to create realistic images in real time. Although CG and image

processing methods used to overlap, both are based on the main operation. Image processing uses techniques to modify or improving existing images such as photos and television scans (Rushmeier et al., 1995). Two major image processing applications are improving the image quality and perceived power of the visual information machine as used in robots. The information presented here shows that volume graphics (VG) can provide the capability to achieve or exceed the quality of the surface graphics. VG has become an independent graphics technology. VG's overall purpose is to achieve a realistic photographic image. In order to achieve this purpose, various reflections, refraction, perspective and shadows predictions are required, and of course can be carried out in the natural environment (Marschner and Shirley, 2015). In VG, VD containing multiple volumes or voxels generally represents objects. Additionally, researchers believe that VG can create similar to the high-quality images obtained on surface support. In last decades, volume visualization (VV) has evolved into an effective technology for VD representation, manipulation, and demonstration. Unlike traditional graphics methods, 3D objects are approximated by polygons, lines, and VD as geometric boundary surfaces, and are 3D objects that may have information (Yagel and Kaufman, 1992). These volume units may be too large to be geometrically represented. The VV approach provides a mechanism for identifying and studying internal or invisible VD structures as well as visually visualizing transparent and complex datasets (Goss, 1994; Kaufman, 1996).

Lorensen and Cline (1987) have aimed to issue the 3D surface models of relevant areas by using the VD obtained with medical imaging methods such as MR and CT. The method used by them is the "Marching Cubes" algorithm. "Marching Cubes" algorithm is determined as a method from which quick results can be obtained in the formation of 3D data compared to the process time, structure suitability, and other algorithms (Chan and Purisima, 1997; Cignoni et al., 1996). In order to classify the multivariate data visualization methods, Kehrner and Hauser (2013) performed detailed analysis in their studies. Urban and Tester developed an

algorithm in order to process 2D data in the current data for obtaining 3D prototypes in MR data. They transformed data to 3D by using various image processing methods (Urban and Tester, 2009). Today, almost thirty voxel models are obtained by using the CT and MR images and thirteen of them have been developed recently (Johansson et al., 2012; Lee and Lee, 2006). The reason for the continuation of construction of voxel models is to obtain models with more realistic and correct organ doses. Thus, the uncertainties about the dose calculations performed by the models shown mathematically will decrease.

In recent years, VV has attracted the interest of researchers (Alakkari and Dingliana, 2016; Arbelaiz et al., 2017; Ebert et al., 2017; Zhou et al., 2015). The VV collection extracts meaningful information from a large number of datasets and displays their 2D images (Kaufman et al., 1993). The datasets are not in the form of a polygon, as shown on the surface of the graphic. On the contrary, the point called the voxel of the 3D grid is an object. Used to analyze VV methods and create conditions that are derived from a variety of sources, including scanners, computer screens on natural and synthetic conditions for medical and simulation results render from 3D datasets. VV becomes a significant dosing schedule for scientific data, such as visual controls derived from MR and CT voxels derived geometric patterns. VV has been widely used in technical sciences and scientific applications in the medical sciences (Alakkari and Dingliana, 2016; Kehrer and Hauser, 2013; Preim et al., 2016).

In all previous applications, the rendering algorithm should be able to extract wholly the according features. For example, the feature could be a more specific tumor that may appear on a mammogram, a shock wave may occur when the liquid is present or present on the smooth stimulating geometric surface. CG continues to develop, and researchers focus on developing volume or rendering modeling procedures (Guérin et al., 2016; Manteaux et al., 2017; Rizzi et al., 2014).

VR can be greatly accelerated by traditional methods such as ray casting and splatting (Çalışkan and Çevik, 2015; Marschner and Shirley, 2015). The goal of the

VR algorithm is to make the 2D image as accurate and effective as possible (Marschner and Lobb, 1994; Bentum et al., 1996). Algorithms of VR can be performed in the form of pipeline. VR has a simple method of operation and simple visualization of the object within the mechanism (Marschner and Lobb, 1994). However, the size of these volumes is large, even if the most powerful coprocessor machines in these environments do not provide the required interactivity. Many datasets come from diagnostic images, numerical simulations, and scanning techniques. For example, MR, CT and ultrasound scanners create 3D ultrasound meshes that are anatomical sites of the human body. Another source of 3D data includes 3D hypertexture (Perlin and Hoffert, 1989) and dynamic simulations, such as seismic sciences, computational fluids, and computational chemistry. Similarly, an algebraic object defined as a sphere can also be included in a 3D grid (Shah et al., 2016). In some of the documents presented, the main focus is on the development of basic algorithms. Splatting (Westover, 1990) is one of the well-known virtual reality algorithms that restore the target grid functionality. Levoy (1988) introduced a detailed surface rendering algorithm. The surface observation method from a given VD is to apply the surface detector to the sample mask and then display the original pattern. For VV, classification has to be determined shape cues and properties of the material. The density of the material is assigned by calculating the transfer function.

VR is consecrated to the growing of transfer functions for some applications (Yagel and Kaufman, 1992). Research has been performed to optimize the basic algorithms using advanced algorithmic methods and implementations of real-time hardware. In the paper presented by Lacroute and Levoy (1994), this new algorithm provides almost an interactive display speed without significant mass loss. The literature describes various VR algorithms, including direct VR (Levoy, 1988), direct surface rendering (Jones, 1997) and variants thereof as a method of predicting maximum intensity (Avila et al., 1994) and, Levoy (1988), defines two transfer functions. There are the operators to detect iso-value shape surfaces and the regional boundaries. The surface value is displayed as opaque, indicating that all voxels have

values that exceed some thresholds. This creates a 3D area of opaque voxels whose outer layer is the desired iso-value surface (Song et al., 2017). The benefits of this transfer function are more common and can be applied to many medical datasets. One of the disadvantages is that the user must specify the appropriate threshold. Levoy's second function for this area interface is specifically designed for volumes of medical CT (Levoy, 1988). It works to assume that there is no more material in the volume than the other two substances. When the material is placed in rising order of its threshold, the material involved in the volume must be neighboring to the ordered list (Zhang et al., 2016). Medical tomography CT is usually bones, skin, and air, so no material touches for more than two others without contact with bones and air (Winter, 2002). The advantage of this method is that it results in information limit values in the CT datasets. One drawback is that the user needs to know the correct threshold and its coverage. The maximum intensity prediction (MIP) algorithm is a standard alternative VR (Avila et al., 1994). A regular ray-casting method is used, but only the biggest intensity value detected along the ray is used to determine the intensity of the pixel, not the integral of all color values and opacity recorded (Liu et al., 2017). In this case, the word intensity can be at a point or as the original value of the data in a dataset is considered opaque. The result of applying the MIP algorithm is similar to that of medical radiography. Figure 1.1 shows the use of MIP before the left and top (Winter, 2002) of the dataset CThead display.

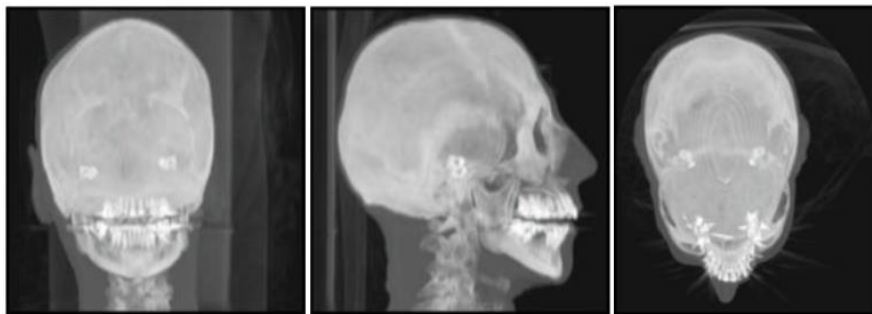


Figure 1.1. Representations of the projection of the maximum intensity of the CThead

The algorithms that use the spatial data structure can be divided into two categories according to the order in which the data structures intersect. The image order algorithm models ray casting of each pixel in the image and performs a voxel process for each ray (Hong et al., 2005). The disadvantage of this process is that the spatial data structure must intersect each ray once. In contrast, the object order algorithm is executed by splatting voxels on the image, whereas the VD in the order of storage transmits them (Westover, 1990; Laur and Hanrahan, 1991). This process sequence makes it difficult to execute the ray early. Levoy (1990) presents an efficient optimization of ray-casting algorithms.

Ray-casting algorithms are often referred to as image order algorithms (Hong et al., 2005). In the ray casting algorithm, the source space is the source dataset, and the target space is the new resample grid. The value of the function as an intensity has to be resampled to the target grid. The basic algorithm is an object sequence algorithm or an image order algorithm (Westover, 1990). Samples and sprays are examples of object-oriented algorithms (Çalışkan and Çevik, 2015). An example of an image order algorithm is ray casting. The object algorithm converts the volume and projects it onto the screen. This function is executed in the image space. The value of the function is restored in the image order algorithm, and the presence of the structure is detected.

Several studies have shown that reconstruction filters estimate functions and their derivatives (Goss, 1994; Little et al., 2016; Marschner and Lobb, 1994). Color and opacity have to be reproduced in the middle of the order of visibility. That is attained through the using the reconstruction function. Researcher exhibit artifacts, but suggested measures and smoothing are useful for designing appropriate filters. However, these measures are not applicable to determining the accuracy of the sample dataset in the interpolation or filter mode. Soft shadow based on shadow volume algorithm for hard shadows (Crow, 1977). The volume of the light source produces so-called soft shadows. There is a smooth transformation from no shadow to full shadow. In the case of hard shadow created by the point source, the conversion

occurs very quickly. Soft shadows are more realistic than hard shadows because all light sources are capturing areas or volumes. Fast rendering of the soft shadow have been studied for decades (Ali et al., 2017; Assarsson and Möller, 2003; Guennebaud et al., 2006; Selgrad et al., 2015). Crow (1977) is used to the shadow volume algorithm a stencil buffer. This shadow has become widely used as advanced graphics equipment and has become the main extension of the algorithm. This algorithm extends the algorithm of the hard shadow volume of the Crow, using 256 levels of shadow intensity. The processes shaded objects, such as the Crow shading algorithm, which is commonly used for hard shadows with special quality constraints for complex scenes (Mora et al., 2016; Sintorn et al., 2014). Shadows are an important factor that improves realism and provides important spatial features (Wanger et al., 1992). For example in Figure 1.2, there is no shadow, and it may be unachievable to determine whether the object is on the ground or close to distance above the ground.

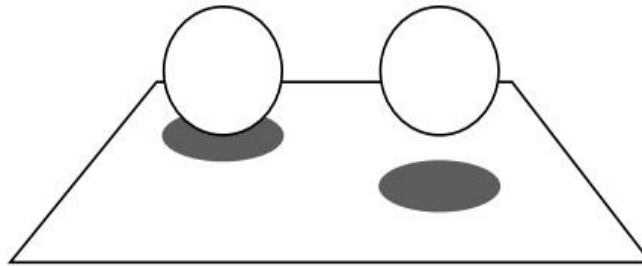


Figure 1.2. Shadow as an example of the importance as spatial cues

In CG, hard shadows and soft shadows are usually divided (Selgrad et al., 2015). In hard shadows, the transition from no shadows to full shadows is immediately on the edge of the shaded area. For soft shadows, the changes are smooth (Wanger et al., 1992). Hard shadows can only be produced by endlessly small light sources, and they do not really occur (Li et al., 2016). All true light sources have a surface or volume that leads to a soft transition called penumbra (Bülbül and Wee, 2016). The soft area can be very small. A hard shadow is therefore

sometimes a reasonable estimate. The full shaded areas are called Umbra. Soft shadows usually improve perceived realism against hard shadows (Rademacher et al., 2001). Hardness also allows shadows to be interpreted as geometrical features. Figure 1.3 shows soft scene shadows, hard shadows, and no shadows (Marschner and Shirley, 2015).

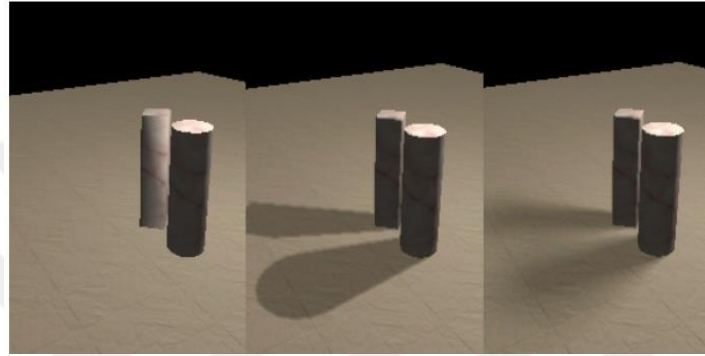


Figure 1.3. No shadows, hard shadows, and soft shadows

Some researchers represent a cell traversal algorithm for the traverse of voxels. Which requires only one flow point addition and two velocity comparisons at each step, also relatively inexpensive based preprocess rays containing up to 40 floating-point operations (Amanatides and Woo, 1987). Its method calculates the point where the beam intersects each cell along its path. Lately, many traditional CG applications, like computer-aided design and modeling, are visualized, modeled and manipulated using VG volume technology (Agoston, 2005; Angel, 2013; Çalışkan and Çevik, 2015; Liu et al., 2010; Marschner and Shirley, 2015; Roth et al., 2016; Taylor et al., 2016).

1.3.1. Volume Graphics

VG is a CG subfield that deals with environments over the 3D volumes created and the representation of such environments (Leu and Chen, 1998). VG deals with modeling, manipulation, and representation of geometric objects through

volumetric displays and VR methods (Çalışkan and Çevik, 2015; Kaufman, 1999). This allows to mix geometric objects with VD under a single volume displays scheme. The 3D scene is transformed into a volume display using the voxelization algorithm before volumetric rendering and modeling methods are implemented (Pantaleoni, 2011).

The visual representation of the data and the 3D datasets is an important part of the medical and scientific discipline (An et al., 2017). Raw data contains many invisible details unless it is appropriate. Visualization technology is under development, and such visualization techniques use graphical primitives to provide alternative views (Asadi et al., 2016). These views take out detailed info from the raw data. In this process, there are two main stages, the modeling of volume and VR (Kaufman et al., 1993; Guthe and Goesele, 2016). In the modeling of volume, the raw data are represented in an intermediate form for processing the downstream display data. In the VR, the displayed data are then scanned to produce an image, which can be projected on the screen (Gill and Gupta, 2015).

VR is a set of methods to represent the 2D projection of a non-visible 3D sampled dataset (Levoy, 1988). A sequence of 2D slices acquired from CT and MR. Subsequently, 3D was reconstructed in a model and displayed for diagnostic planning or purposes for surgery and treatment. There are several numbers of image pixels in the regular pattern. This is an example of a volumetric grid where each volume or voxel element is represented by a single value. This is achieved by sampling the area surrounding the voxel (Yagel et al., 1992). To render the 2D projection of a 3D dataset firstly needs to determine the camera in space relative to the volume (Lin et al., 2013). In addition, it is necessary to determine the opacity and color of each voxel. This is generally determined using the RGBA function (red, green, blue, alpha), which determines the RGBA value for each reasonable voxel value (Gill and Gupta, 2015).

The general goal of VG is to get a photorealistic vision. To reach this purpose, shadow, refraction, reflection, and perspective projections are needed, as

they occur naturally in a physical environment (Perard et al., 2017). In recent years VV has been developed as a powerful method of rendering, representation, manipulation and VD (Arbelaiz et al., 2017; Lamar et al., 2000; Perard et al., 2017). Unlike conventional graphics techniques, 3D objects, such as the surface and the geometric surfaces, typically approximated by polygons and lines represent VD units, which may have information (Pfister and Kaufman, 1993). These 3D elements cannot be made up of surfaces and edges. VV methods provide mechanisms for detecting and examining internal or invisible VD structures and providing visual information in transparent and complex datasets. VV is a method of extracting important information from VD using interactive graphics, images, and concerns the presentation of VD, modeling, rendering, manipulation and representation (Agoston, 2005).

Continuous volume shapes can also be created from polygon data, such as 3D grids (Choy et al., 2016). Generally, this is done the input mesh domain by voxelization. And then, the mesh is traversed using a sampling box. The concentration in the current frame is added to the voxelized object based on the concentration values in the sampling box and the current criteria (Jiménez et al., 2014). The advantage of this representation is that any polygon surface can be represented within a 3D object, so volume operations can be performed on the voxel grid. The voxelization depends on the size of the sample box and the disadvantage for the output. A smaller size of sampling box leads to a more uniform voxelization, but memory requirements increase enormously (Schwarz and Seidel, 2010).

The volume simulation is also shown in the frequency domain. Initial approaches include a programmed Fourier method and a method of morphological transformation based on the wavelet, which divides the volume into a series of frequency bands (Mishra and Sahai, 2013). Unfortunately, these suffer from high-frequency artifacts introduced during interpolation. Volume deformation can be modeled with ray deflectors. In this case, the ray is converted rather than the volume by rotation, scaling, and discontinuous operators (Correa et al., 2010). Since the

research data is limited to the sphere, it is difficult to achieve topologies that are more complex in the absence of spheres with different radius.

By introducing hardware 3D surface mapping, texture modeling based on volume mapping and volume deformation have been researched in (Herrera et al., 2014; Newcombe et al., 2015). The method uses a tetrahedron reproduction. The model requires additional preprocessing time to extract the tetrahedral structure (Moses et al., 2010).

A nonphysical method of expressing the volume in the form of a chain-rings is also proposed. In this way, the deformation is limited by constraints (Aguilera et al., 2015). Nevertheless, the basic model of deformation using this method is not physical. Alternatively, using skeletal data, the tree skeleton model is used as a deformed bone (Khoo and Chung, 2017). However, this result leads to extra preprocessing operating expense.

A significant step in modeling and reconstructing the volume is the missing of data approximation of known data for interpolation. Buoncompagni et al. (2017), has studied the shape interpolation of multidimensional objects. Unfortunately, this method does not apply to fuzzy datasets, because this method is based on complex classification. The datasets are common in medical and scientific applications such as imaging of the microscopic. In order to reduce the interpolation artifacts, Chun et al. (1991), have developed a 3D interpolation algorithm using locally obtained information. Later, this approach has been developed using visualization of higher order derivatives and basic curvature, based on the iso-surface in VD. The differential dependency makes the method very sensitive to noise. A dataset with a low pass filter is required (Albin et al., 2016). Then direction is included in the formula interpolation, which is estimated using the structural tensor obtained from the eigen analysis (Dhou et al., 2014; Zhang et al., 2017). In order to minimize the overall curvature, the conjugate gradient method is used (Patel and Ghodgaonkar, 2017). This facilitates to smooth the interpolation, which provides an accurate extraction of the isometric. All these approaches are based on formal interpolation

in one way or another. On the other hand, the identification of shape is not always possible for the fluorescence datasets, which are obtained (Zhang et al., 2016).

Construction of incomplete signals by means of nonlinear interpolation was carried out in different disciplines. The initial method uses a genetic algorithm to extract the Fourier coefficients (Tao et al., 2015). B-spline interpolation is used for gradient estimation of accurate gradients for shading and for extracting features with an adaptive bi-directional flow (Köhler et al., 2017). Artifacts are eliminated by normal diffusion in the tangential direction, and image characteristics are protected (Park et al., 2017).

1.3.2. Volume Rendering

In recent decades, VR has become a popular visualization tool in medicine, biotechnology, engineering and many other sciences (Sugihara et al., 2017). Although the properties of VR provide an invaluable advantage, the lack of interaction refresh rates, the use of this area in the past is limited (Wang et al., 2015).

In the 1970s, the first of the VR technique in the Mayo Clinic (Calhoun et al., 1999) was performed. Later, in the 1980s, due to improved manipulation of data transmission technology and image processing hardware, the VR algorithm in a parallel processing system could be implemented (Kehrer and Hauser, 2013). VR is the first parallelization algorithm at the University of North Carolina and Pixar. 3D rendering - work in the 1990s was greatly facilitating the acceleration of graphics hardware from Silicon Graphics in Mountain View, California developed (Preim et al., 2016). The software developed by Silicon Graphics optimizes their use in the medical aspects of the method of displaying a special texture (Calhoun et al., 1999).

The great importance of VR is their use in scientific visualization (Çelebi and Çevik, 2010). One of the main goals contributes to the rapid development of medical imaging and image processing microscopy, CT and MR (Gill and Gupta, 2015). In addition, VR technology in geological exploration, climate analysis, molecular modeling and other fields of science can be applied (Fei and Xia, 2010).

VR with a set of 3D image data is an important area of clinical research and sciences (Murphy and Atala, 2014). The 2D image generated by VR algorithm is transparent, and the color is mentioned in the place of their actual color. VR requires the first way of sorting processing, assigning different areas with different color and transparency coefficient. Then, according to the display and the position of the data set, the algorithm will determine the effect of the final image (Eid et al., 2017). A number of operations are employed to the received data to obtain a VR. This series of processes is usually called the VR pipeline (Jönsson et al., 2014; Kindlmann et al., 2003). A regular pipeline is shown in Figure 1.4.

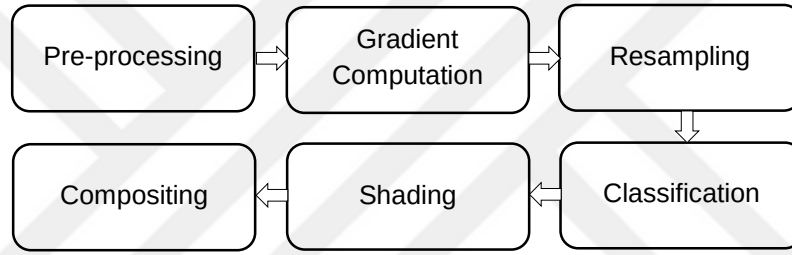


Figure 1.4. A regular VR pipeline

The process begins with the application of preliminary processing of the received data, which can include noise reduction by using a low-pass filter in the data. It can also include segmentation to isolate areas of interest to the volume. Gradients of VD are usually calculated using finite difference methods. Then, the resampling stage can then be applied to use certain interpolation methods to obtain the intensity values at the middle of the dataset. The classification can then be performed by applying the transfer functions to the dataset. Different voxels are obscured by the desired shading pattern. Lastly, the resulting voxels are arranged in order of depth to get the rendering.

A natural way to do VR process in the grid is to use a Cartesian Cubic (CC) grid (Finkbeiner et al., 2010). Voxels in the equidistant grid CC are shaped like cubes (Figure 1.5).

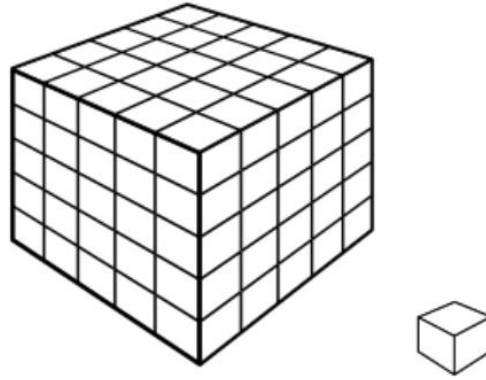


Figure 1.5. CC cubic grid and one voxel

For 3D visualization, one of the techniques VR methods, marching cubes, or dividing cubes can be selected. VR takes longer than others (Silva et al., 2005). Dividing cubes are more suitable for images based on software. Typically, based on marching cubes, a technician for the image of polygons or hardware is preferred if the motion process within the surface removed is performed (Lorensen et al., 1987). The Marching Cubes method is based on the principle of scalar polygonal areas that are scanned numerically between sections with logic separation and character of the process of 3D data (Newman and Yi, 2006). It is ensured to divide such sampled areas into cubes consisting of 8 volumetric points and determine whether these points remain within co-surfaces. In the basic cells that have an octagonal, 256 different conditions are being considered (Roy and Augustine, 2017).

Scientific visualization is a technology and calculation technique (Alakkari and Dingliana, 2016). It uses knowledge in CG, image processing, and computer vision to transform symbolic and digital information into geometry so that researchers observe the result of the calculation (Kehrer and Hauser, 2013; Preim et al., 2016). It can bring enormous benefit to scientific productivity and maintain the potential for scientific progress. VR is a subsidiary of scientific visualization. It is the method by which a 2D projection image is generated from a set of 3D data. Comparison with other methods of scientific visualization, the ultimate goal of VR is to display 3D details in the image plane. For example, if a house is used as a 3D

volume in a house, there are furniture, appliances and other items (Xue et al., 2016). When the user sees the house from the outside, it can look only externally and layout the design of the room or remove objects; but if the house and the objects are semi-transparent, all the details can be seen the same time.

VR is a general term for visualizing VD imaging techniques and includes methods such as ray casting (RC), shear warping, and splatting (Moraes et al., 2017). Of particular interest is RC, so the visualization of the interior of objects in the record and are complex objects like the skeleton and muscles (Borzecki et al., 2014). The RC representation method is the most studied VR method based on images because of its high quality of the result and its ability to achieve a transparent effect (Roth, 1982). The idea of RC algorithm is very similar to the transmission of light in the real world, but it is carried out in the reverse order. In nature, a light source emits a group of rays of light through a transparent object. Some rays fall on the eyes and the image on our retina (Arbelaiz et al., 2017). In the RC algorithm of rays are triggered from the eye to the image plane, one per pixel, and find the intersection of objects blocking the path of each ray. Lightning ends when another object does not fall in the path. During the transfer of the object, the color value is selected at a certain interval along the beam.

Appel (1968) introduced the first RC algorithm. It was this article, in which the basic idea of sending rays from the camera appeared, one by one per pixel. The color of the pixel is determined by determining whether the beam intersects the object. The first method, it can be used as a volume RC appeared (Kajiya and Heart, 1977) defined, but was not accepted until 1988 for Levoy he published an article that became a modern definition of the term (Levoy, 1988). The main object of RC volume to 3D is to transfer object data (Preim et al., 2016). It is easy to extract the surface of the mesh object of other algorithms, such as Marching Cubes, which RC amount of information can be visualized over the object. This well-used function in medical imaging can improve certain specific or liquid data, where the data is displayed partially transparent. Both RC and ray tracing (RT) can create very

realistic rendering, but with high quality, it has a high price. This makes these methods best suited for shooting ahead of time and not in real time visualization (Schäfer et al., 2014). In the case of the volume RC algorithm, when the ray intersects the object, the ray continues to move in volume. This algorithm also requires a volume dataset to find out what is within the volume. There are four basic steps to create this algorithm (Pfister and Wittenbrink, 2000). These steps can be seen in Figure 1.6 (Figure taken from Wikipedia under title: Volume RC).

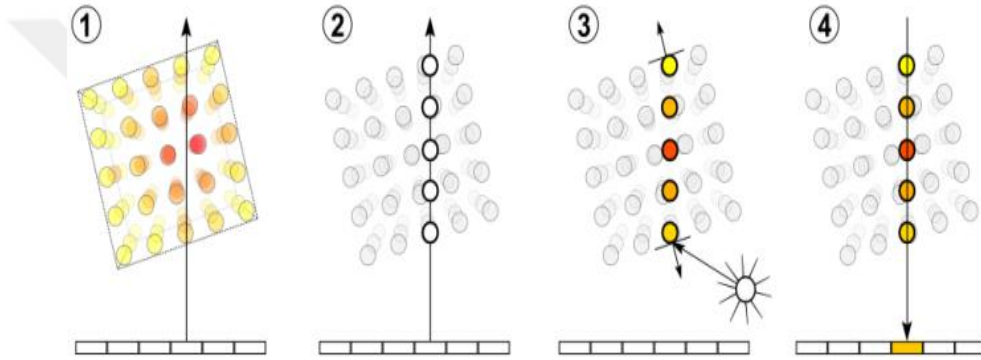


Figure 1.6. The four basic steps of the RC volume: (1) RC (2) Sampling (3) Shading (4) Composition

The amount of RC data is viewed as a gaseous cloud and the representation of the cloud. These are based on a model of physically plausible lighting from the user's perspective (Izadi et al., 2011). The camera is located in the user position, and the ray passes through the camera screen emitted for each pixel of the image presented (Figure 1.7).

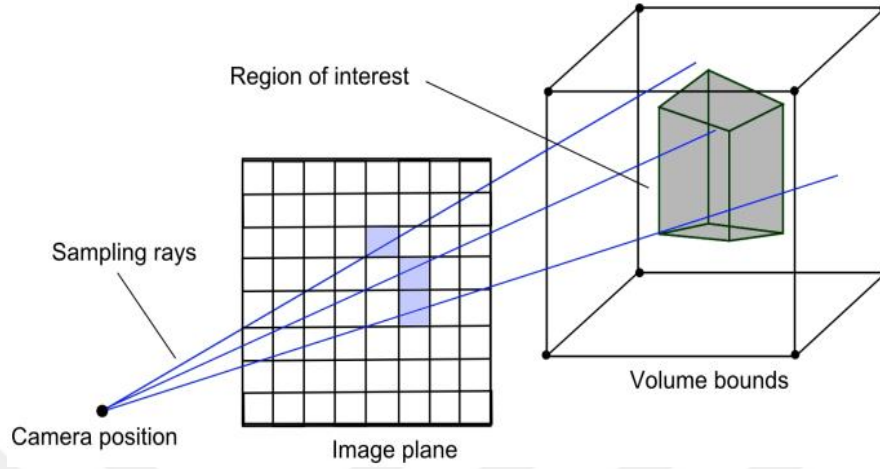


Figure 1.7. The main RC volume

The restriction of the RC algorithm is its mass calculation. The advantage of this algorithm shows a parallel character in VR. Therefore, RC is studied for its acceleration in special equipment for rendering. Before the graphics processor unit (GPU) was able to perform tasks such as hardware rendering tools like volumePro (Pfister et al., 1999), it is widely used in this field. Recent studies have generally accelerated VR technology as RC in a modern GPU (Gill and Gupta, 2015; Silva et al., 2005; Sugihara et al., 2017). In the past, based on voxels like volumePro VR software it works very expensive, usually on SGI workstations. In the 2000s, the GPU rendering speed can be achieved at a low cost. Thus, many research organizations, software products of virtual reality began to develop. These Voreen programs at the University of Münster developed VolView developed by Kitware and Voxx from the University of Indiana developed (Meyer-Spradow et al., 2009; Sharp et al., 2007). These image processing programs were developed to use business graphics processors like GeForce and Radeon. However, this does not at all mean the VR's software capability of the GPU to combine image processing in 3D execution (Cuomo et al., 2014).

RT, which volume RC is an option, is essentially an attempt to imitate nature. The colors seen in the eyes come from the light rays emitted by the Sun,

swinging around the world and finally reaching the eye (Kehrer and Hauser, 2013). RT performs this operation in the opposite direction. Since the rays of the eye to be sent to the scene, and when the ray touches the point on the object, an additional ray is transmitted. This ray is the ray of the shadow and moving from the point of the object in the direction of the light source. When the second ray of the light source reaches, the cut off with another object without, the point should be illuminated by the source, and when the object is in the path of the ray, the point is in the shadow of light (Ament et al., 2017). This can be seen in Figure 1.8 (Figure taken from Wikipedia under title: RT).

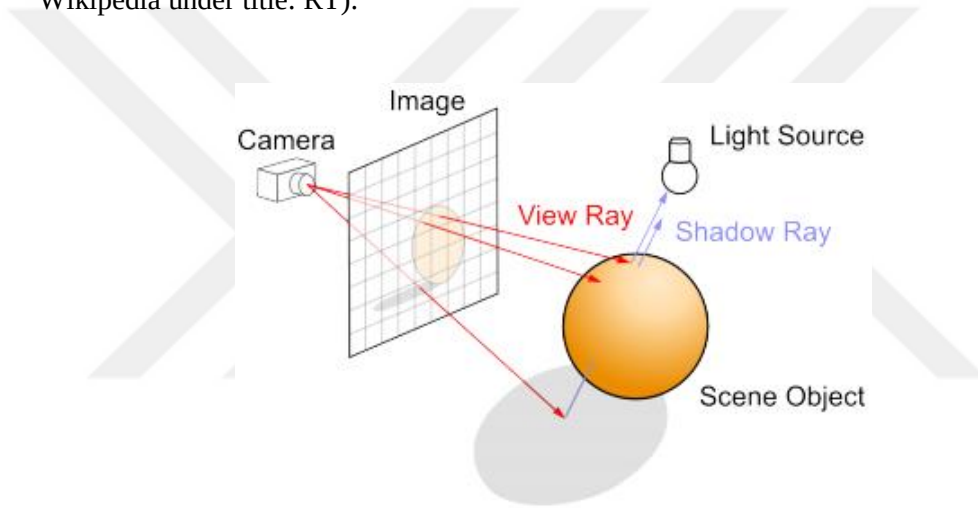


Figure 1.8. The RT algorithm builds the image of the rays passing through the scene

The first step is to send out a ray, for each pixel, which will intersect with the volume same as in RT. The next step is to create some discrete points along the ray path to capture the RV. These points are often a predetermined distance between them and, as a rule, are not aligned with the view and are often placed between voxels. To account for this, the values of the surrounding voxel are interpolated to get the correct value for the point. This value is used in the next step, shading. The voxel corresponds to the position of the light source and the density in the volume between the voxel and the light source (Özyıldırım and Çevik, 2017). Since the location is known, all that is required is density. As in the case of the RT

algorithm, the shadow ray is sent to a light source to see that the voxel is shaded and to move the volume to calculate the density. With this information, all sampling points along the path of the ray are shaded. This will create a 3D grid color values used in the next step. The final step of the algorithm is to combine all of these sampling points and the background in the final color for use in the pixel. This step is called composition and creates a 2D image of 3D voxel values (Goswami and Misra, 2015). For each voxel, a ray of two crossed values was required, the first one the shaded color of the lighting model, and the second the opacity value for the specific contents of this voxel. These two values are then combined with the final pixel intensity. This technique will benefit and other properties when visualizing the simulation (Herrera et al., 2014). The technician is visible voxel projected from the specified address; it means that the VD can be seen from any direction (Guthe and Goesele, 2016). In addition, sampling points within the volume exist, and all data is colored separately, the user can decide whether the data is expanded or removed. This provides a function that you can see the difference in the value of the data or the surface is compressed to see otherwise, for example, a pearl inside a box. The RC speed may depend on many different factors, such as the default screen resolution, volume size and volume increment (Wu et al., 2017). These are designed for the most static variables, which can significantly affect the efficiency of the algorithm. However, methods have been developed to speed up the process, for example, stopping the early ray and jumping empty space.

1.3.3. Fractal Geometry

Fractal geometry provides to obtain rich graphical images by courtesy of the mathematical iterations that can be performed by a computer (Çalışkan and Çevik, 2017; Kenkel et al., 1996).

Another property of fractals is the property of self-similarity, which we commonly encounter in nature. A fractal figure that is formed by any iteration system

occurs by various successive iterations of the same mathematical formula core (Mandelbrot, 1983). A sample fractal image is shown in Figure 1.9.

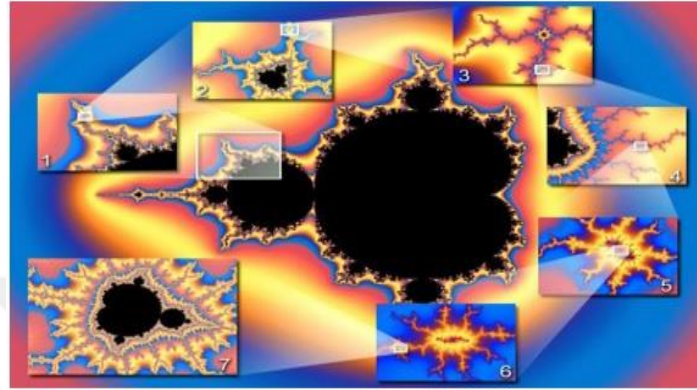


Figure 1.9. A sample of fractal geometry iterations

In order to transfer the complex objects to the 3D, the fractal geometry and the box-counting method of the fractal geometry have been used at the present time (Liu et al., 2014; Milošević et al., 2017). Fractal geometry produces applicable solutions in structure modeling of the irregular pieces in the universe. It is used widely for the modeling of the materials to be produced aesthetically in architectural and engineering applications (Kenkel and Walker, 1996; Cross, 1997; Heymans et al., 2000). The box-counting method was used in order to provide the analogy and comparison of 2D images as 3D (Jennane et al., 2007). Fractal geometry provides sensitive results for transferring the data to the 3D and smooth ones after modeling. A 3D figure displays the fractal geometry sets with options. In addition, the presentation of the existing medical imaging data, and some relevant values (Hausdorff Dimension) and their transfer to graphics were carried out. In the next step, transferring processes to the 3D were applied. One of the most significant points at this part was to realize the use of the medical images in a data set for such transferring process to the 3D.

Figure 1.10 illustrates the algorithm, the contour specification method of which has been developed with the fractal bases. As a result, compared to the current histogram structures and contour specification data, more sensitive and measurable results were obtained (Zhu et al., 2010). Flowchart of the contour specifying algorithm of the image is shown in the figure.

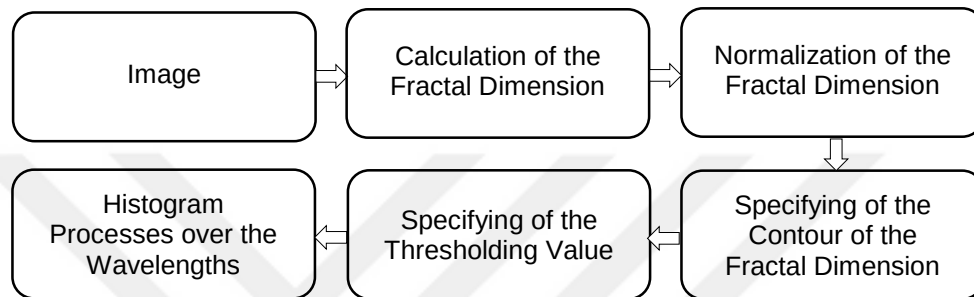


Figure 1.10. Flowchart of the contour specifying algorithm

The parasitism in the images obtained from the X-ray devices was removed with the box-counting method and a fractal method in the required segmentation processes (Wang et al., 2008).

1.4. Medical Imaging Techniques

In the 20th century, there have been significant developments in the field of medicine as well as many arenas, and the quality of services for diagnosis and treatment has increased greatly (Rengier et al., 2010). Following the discovery of X-rays in 1895, gamma cameras in the 1950s (Kantzas et al., 2000), CT in the early 1970s, and the introduction of MR devices in the medical field in the 1980s led to changes in the quality and quantity of devices used in hospitals Filler, 2010). As a result of improvements in electronics and computer technology, the number of high-tech medical devices has rapidly increased in number and variety.

Biomedical devices and biomedical imaging devices are currently used in medical science for diagnosis and treatment. Biomedical imaging devices require an extreme care and attention from the research and development stage to its production

and also after production technical service. The slightest flaw in these devices, which are in contact with the patient in some cases, can have irreversible consequences. These devices, which have to be perfect at the highest level, and tolerance are kept at the lowest possible values, giving the best diagnosis and high perfection. These devices are used in the detection and diagnosis of disease findings (Mariani et al., 2010). Biomedical imaging with the use of these devices; the body region of the patient is examined for various diagnostic purposes. Biomedical imaging is a diagnostic method.

Medical imaging systems used for clinical purposes are based on some basic techniques (Sharma and Aggarwal, 2010; Tsai and Matsuyama, 2015). These are as followings:

1. A method of measuring X-rays passed through the human body.
2. Method of rotation and measurement of transmitted ultrasound waves reflected from various tissues.
3. A method of measuring gamma rays emitted from radioactive materials injected into a vessel.
4. Nuclear MR method based on the principle of exposing hydrogen atoms in the body to high magnetic field.
5. Thermal imaging techniques.

Biomedical devices use waves over a certain frequency (Hoskins et al., 2017). For example; MR devices use radio waves, CT devices use very high and fast x-rays, ultrasonic device sound waves and nuclear medicine radioactive materials. These devices have recently been in medical service and will be used more intensively in the future.

As it can be seen, for medicine and biomedical, the important stages of development in technology have occurred in the last century. Nowadays, scientific developments are transformed into technology and applied to different disciplines in

a very short time. In the near future, studies are being conducted on remote patients, remote surgeries, nano-robots circulating in the body, new drugs and treatment methods (Calin et al., 2016; Deborah et al., 2016; Felicetti et al., 2016). Within a short period of time, new technologies related to health have emerged, such as Rontgen, Ultrason, CT, MR, and nuclear medicine imaging systems, color ultrasonic fiber endoscopes, various types of laser devices, and many other health related technologies (Ilangovan et al., 2016; Neuman et al., 2012).

1.4.1. Rontgen

X-rays are a method of imaging structures, especially bones, using X-rays (Hoskins et al., 2017). It is also the oldest of the radiological diagnostic methods. Used X-ray (Izadifar et al., 2016) is similar to visible light or radio waves in nature. X-rays consist of energy waves that can travel in space (in vacuum) and pass through certain substances. The X-rays are invisible to the naked eye, and the electromagnetic spectrum is located between the ultraviolet and gamma rays. In 1895, Wilhelm Conrad discovered X-rays (Lischalk et al., 2016). Therefore, these rays are also called Rontgen. Rontgen observed two events when experimenting with the electric current through a vacuum lamp, in which most of the air was evacuated. The first one was that the rays from the cathode (minus the pole) towards the anode (plus pole), which were thought to have formed from very small particles, and the second one created a green fluorescence on the glass when they hit the layer of phosphorus plastered on the other end of the lamp.

The main feature that allows X-rays to be used in diagnostic radiology is the ability to penetrate the tissue (White and Pharoah, 2014). Unlike other rays, X-rays pass through the tissues and reach the opposite side in different amounts according to the softness or stiffness of the tissues. This feature of X-rays is used in roentgens. Since the human body is made from various atomic weights and tissues of different thickness and density, the absorption of X-rays will also be different. As a result of different absorption, X-rays falling at different rates on the rontgen film form an

image of the body part that they pass through. This image consists of gray tones ranging from black (the amount of light that falls on the film is high) to white (the amount of light falling on the film is low).

The patient to be X-rayed is placed between the patient's Rontgen tube (X-ray tube) and the patient's X-rays through the patient's body for a short period of time (Figure 1.11). The x-rays from the x-ray tube arrive at the table of the device after passing the patient to be x-rayed. In this table, old type devices have film cassette and new type devices have electronic detectors (Rajasekaran, 2014).

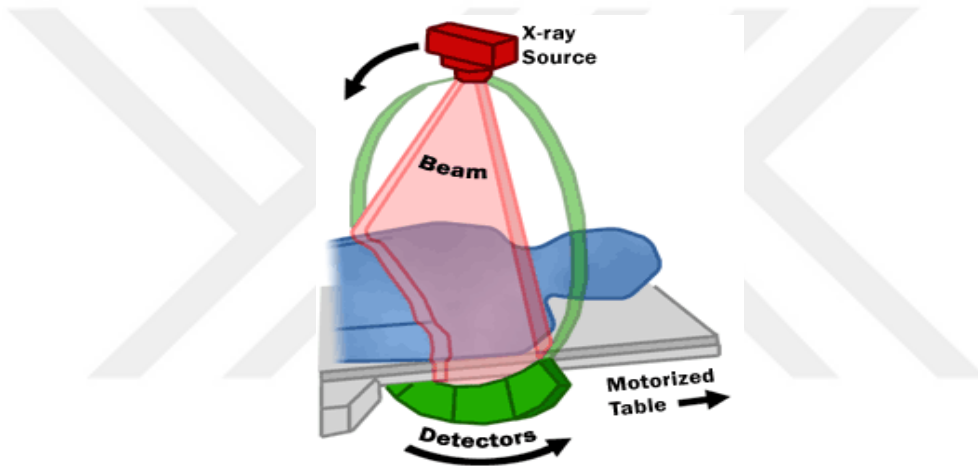


Figure 1.11. X-ray beam projection scheme

The x-rays falling on the film cassette or electronic detector produce color tones between black and white, depending on the softness or stiffness of the tissues. If the texture is soft, it appears blacker than the amount of passing light is more. If the texture is stiff, there will be white tints because the amount of passing light is small. Through to these color tones, an X-ray film of the region is obtained (Figure 1.12).



Figure 1.12. Chest X-ray Image

The image shown in the Figure 1.12 is formed by lowering the passing X-rays of the body onto an X-ray film consisting of a plastic sheet of silver bromide emulsion (Quaia et al., 2013). The silver bromide molecules in the non-irradiated regions are removed from the film and the white plastic base appears. This process is called film processing. So in short, the oxidized silver forms the image in the roentgenograms. This method of obtaining silver bromide images is called conventional digital x-ray, and the way in which the x-rays passing through the body are measured by the detectors and displayed in the cathode tube through the computer is called digital X-ray (Suetens, 2017).

1.4.2. Ultrasound

Ultrasound (US) is a sound wave that is so high that it can not be heard by the human ear (Caon, 2016). It is based on sending high frequency sound waves to the body and detecting their reflections (echoes) from different tissue surfaces. Particularly liquid filled structures display very well. For the first time in 1942, Theodore Dussik described a medical ultrasound (Waingankar et al., 2015). A 2D ultrasound was invented with developing technology (Waine et al., 2015). For the first time, Ludwig and Struthers showed the stones in the bile duct with the help of sound waves that the ear cannot hear (Ghoshal et al., 2013).

Unlike X-rays, sound is not electromagnetic. Ultrasound is an acoustic wave in solid, liquid or gaseous medium. An environment is necessary for the voice to be transmitted, and the propagation is a form of energy transfer from one place to another. The rate of propagation of sound waves depends on the density of the environment (Caon, 2016).

Ultrasonography is similar to X-ray, CT, and MR because of its relying on echo bases (Kramer et al., 2017). Ultrasonic can distinguish between the interfaces between different acoustic density soft tissue structures. The intensity of the reflected echoes depends on the acoustical interface and the angle of the sound beam. The closer the angle of incidence of the sound beam is to the perpendicular, the less the sound is reflected. If there are more than three deviations from the perpendicular angle, the sensor cannot catch the reflected sound (Cosgrove, 2017).

Ultrasound can pass through organ and soft tissues well and cannot be transplanted in air organs such as the gastrointestinal tract (Jain, 2015). Since the bones do not penetrate the ultrasound, the organs surrounded by the bones are examined by ultrasonography. The intensity of the ultrasonic wave is reduced by absorption, reflection and scattering. Tissue absorption increases with increasing frequency of ultrasound wave. When the ultrasonic beam passes from a certain acoustic feature to a different acoustic feature, a part of the sound differs.

Nowadays, 3D or four-dimensional ultrasonography devices have taken place in major clinics (Pfister et al., 2016; Sazonov et al., 2017). The data obtained with this technology is processed with the help of a computer and the result is a 3D image.

1.4.3. Computed Tomography

CT is a medical imaging technology developed in 1970 (Beckmann, 2006). The first CT paper published in 1971 and the CT scanner was used for the first time in the clinical setting was 1972, and frontal lobe tumor was detected using new

technology (Tang et al., 2012). For the history of CT and its clinical application, Kalender can invite readers to review (Kalender, 2006).

CT is a radiological diagnostic method for creating a cross-sectional view of a region of the body examined using x-rays (Liu et al., 2014). With this method, the superposition in the classical X-rays was removed from the center. The images are much more detailed than the X-ray. CT is the product of the combination of X-ray and computer technology. In order to be able to create a CT section, it is necessary to know the X-ray attenuation value of each point in the plane of the section. These values are obtained by processing a large number of measurements made by passing X-rays through the cross-sectional plane in all directions with powerful computers. These numerical values that are found are obtained by painting with the corresponding gray tones. CT images are more detailed than X-rays (Asim et al., 2017). There are two main reasons for this. Firstly, it is the display of a thin slice of the body. On the X-ray, the structures in the x-ray passes over the top. For this reason, it is difficult to select constructions, which have no significant density difference between them. This situation has been removed from CT, which displays a thin body slice. Secondly, it is a direct measurement of x-ray retention rates of tissues. Many factors such as film, bath factors (time, temperature, chemicals) are effective in x-ray detection. These factors prevent the reflection of the tissue on the image. This obstacle has been removed from CT. Images are created directly by tapping x-ray attenuation values.

Therefore, CT images reflect tissue contrast much more sensitively. Since the energy used by the method is X-ray, the gray tones in the images are like the X-ray. Dark gray tones show areas where X-rays are less held according to light tones. During the examination, the patient lies without moving on the table of the CT device. The table is inserted manually or with the remote control into the device's gantry opening. The device is connected to a computer. When the X-ray source performs a 360-degree rotation around the patient to be examined, a computer processes the data obtained by detecting the passing part of the X-ray beam by

hollow or gantry detectors. As a result, cross-sectional images of the tissues are created one after the other. The created images can be viewed from the computer screen. In addition, images can be transferred to the film or stored on the optical disk to bring it back to the computer screen when necessary. An example of a possible CT scanner design is shown in Figure 1.13 (Bushberg and Boone, 2011).

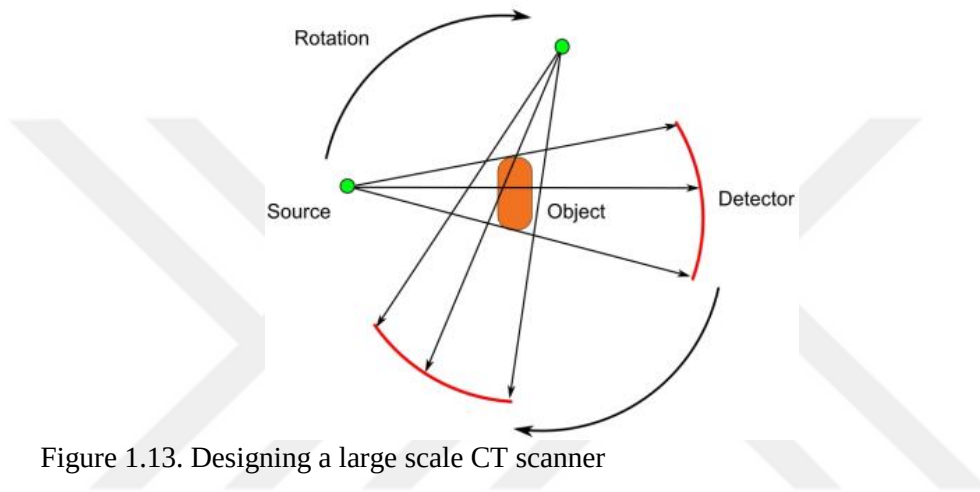


Figure 1.13. Designing a large scale CT scanner

Figure 1.14 shows the cross-section geometry of the CT and a slice of the sample taken. Consecutive cross sectioning is a phenomenon to be investigated by the spiral movement of the detector during the table movement (Webb et al., 2014).

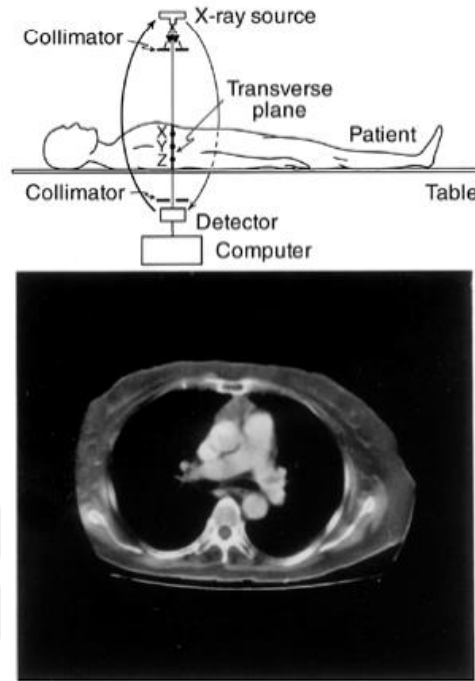


Figure 1.14. A sample of CT slice

Because the CT device receives a cross-sectional image, it provides inter-tissue differences by providing soft tissue contrast that Normal X-ray cannot resolve (Ju et al., 2016). In order to create a cross-sectional image in CT, the operations can be summarized as following;

1. The first condition is that the X-ray tube rotates 360 degrees around the section plane to send a narrow X-ray beam. The X-rays are measured while being transmitted to the body, the body is measured after passing, the difference is calculated, the touching X-ray against the detectors is found, and complex computer processes from these many measurements generate the image (White and Pharoah, 2014).
2. As in all digital images, the image also consists of thumbnail elements (pixels) in the CT. This is called the image matrix. The number of

elements of the matrix is shown as the product of the number of pixels on both sides of the view, and in today's devices, this number is usually 512x512.

3. In CT, images are not actually 2D. CT images have a thickness that is determined during ingestion. The units that are measured in CT are not pixels, but the rectangular prisms of the base of the pixels and the height of the cross-section. This is called voxel, which means the prismatic volume element (Figure 1.15). For example, if the cross-sectional thickness is determined to be 5 mm, in a CT device having an image matrix of 512x512, a pixel size of about $0.5 \times 0.5 \text{ mm}^2$ and a voxel volume of $0.5 \times 0.5 \times 5 \text{ mm}^3$ will be displayed in a 25-cm area (D) image. In modern devices where the cross-sectional thicknesses are reduced to 0.5 mm, the voxel is cubic (Jun et al., 2013).

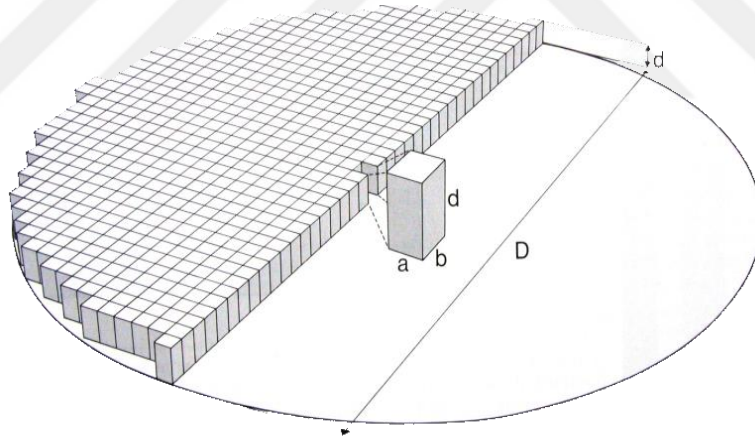


Figure 1.15. Pixel ($a \times b$) and voxel ($a \times b \times d$), D: the diameter of the image area

4. Measurements and digitized values of the detectors are converted into x-ray holding values of each voxel by means of computers. This process is done according to a ruler with a value of -1000 and a value of +3,095, which accepts the value of the x-ray holding value of water (Lamba et

al., 2014). In this chart, scale is called as Hounsfield scale since he is the British physicist Hounsfield, one of the methodologists, and the scales in this table are called the CT unit or the Hounsfield unit (HU) (Figure 1.16).

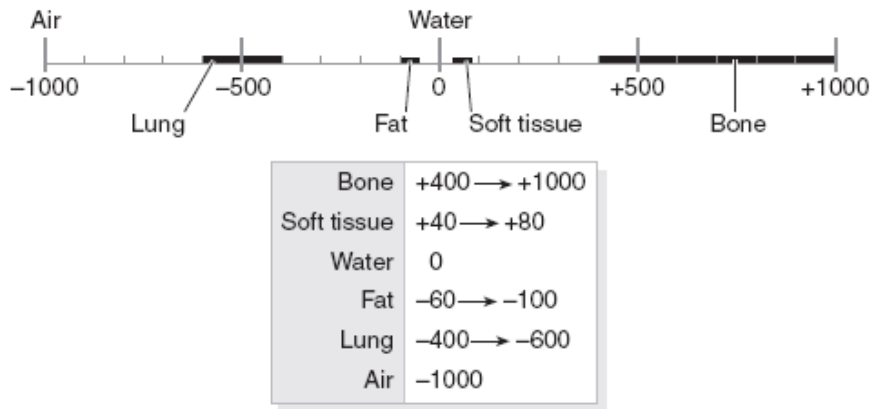


Figure 1.16. The Hounsfield scale of CT numbers

5. The computers of the system give a number to all voxels according to this chart. This number is positive for tissues whose density is higher than water, and negative for low ones.
6. The last action the system will take is to count the voxels with numerical values according to the Hounsfield scale, with black, white and gray tones matching the numbers they get. For this, a gray ruler is used, which is incremental white, minus black (gray scale).

The numerical value of voxel is the average value of all structures that fall within the voxel (Wang et al., 2013). The color of the pixels seen in a CT section is the average color of the voxel to which it belongs. On a digital x-ray, the color of the pixel is the value of the x-ray retention value of the entire thickness through which the x-ray passes. The images on television in our homes are digital, and the color of the pixels is the color of the photos, there is no depth and thickness. Unlike x-ray,

when interpreting images in CT, the thickness of the objects does not need to be included in the calculation, because the cross-sectional thickness is equal on all sides.

1.4.4. Magnetic Resonance

MR is a more commonly used method for imaging the internal structure of living things (Vlaardingerbroek and Boer, 2013). At high levels of magnetism, the living tissue is displayed by the reflection method. Due to its different characteristics, CT can also be supported in the detection of diseases (Filler, 2010).

The MR is imaged according to the density and movement of the hydrogen atoms in the tissue (White and Pharoah, 2014). Radiation is not used in MR, but instead the proton in the nuclei of hydrogen atoms in the body is stimulated by the magnetic field. The signals arriving at the receiver are converted into black and white images by computer analysis. All images are made in digital media and are very different from other imaging methods. In MR imaging, patient positioning, coils selection and placement, protocol creation and graphical grafting schemes influence image quality and correct diagnosis. At the time of imaging, imaging is done with the graphical plans created with the determined protocols (Figure 1.17) (Elsayed et al., 2012).

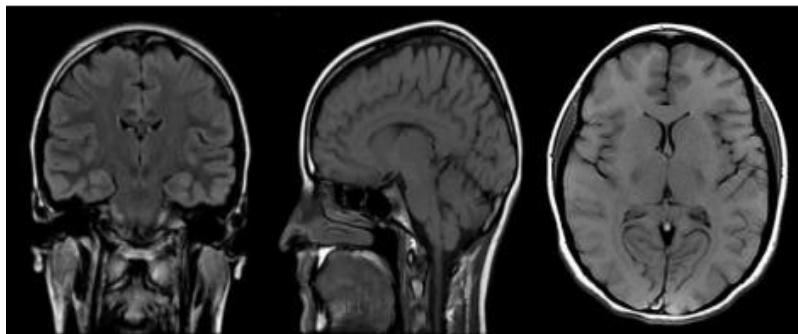


Figure 1.17. Coronal, sagittal and axial view

Today, MR is especially used for imaging soft tissues. It is frequently used in the diagnosis of central nervous system (brain and spinal cord) diseases, athlete

injuries, musculoskeletal system, especially meniscus, belly button, as well as all kinds of neurological diseases (White and Pharoah, 2014). Functional applications that have begun to be used have expanded the scope of use of MR imaging and have transformed a functional examination method from MR imaging to anatomical imaging.

1.4.5. Nuclear Medicine Imaging

Nuclear medicine is a science that deals with the diagnosis and treatment of human diseases through biological and chemical structures marked with radioactive elements (Mettler and Guiberteau, 2011). Nuclear medicine is used for imaging and treatment purposes. Imaging techniques are utilized using radioactive elements. The greatest advantage over other methods is that it also provides physiological knowledge.

Other radiological methods such as US, CT and MR can provide good quality images about the anatomical structure of the desired region (White and Pharoah, 2014). Nuclear medicine methods have knowledge of the function of the organ, taking into account the rate of uptake by the radiopharmaceutical organ and the amount of body cleansing (Mettler and Guiberteau, 2011). Nuclear medicine, for example, can show the amount of blood flow in the heart, brain or kidneys, or the areas of spread of tumoral tissue within the skeletal system.

Diagnosis, treatment and follow-up of serious illnesses are possible with nuclear medicine methods (Cherry et al., 2012). Generally, diseases can be detected by nuclear medicine methods before they become detectable by other radiological methods and before the clinical manifestations develop, that is, early in the disease. Thus, the disease can be treated without further progress and more successfully. Nuclear medicine is usually used for diagnostic purposes, but it has an important place in the treatment of diseases.



2. MATERIAL AND METHOD

A 3D surface model was constructed utilizing 2D medical image data which has been obtained from different positions of the CT machine. Subsequently, the model was tested using noise detection techniques, including ELM and several filtering techniques. The adjustment of contrast and the brightness of each CT section was then performed utilizing noise detection and image processing techniques. After finding the similarities of the 2D images, the shifting distance between the images was calculated by applying edge detection algorithms. The 3D surface model was obtained by applying VR techniques. The 2D images have been tested for denoising using different filtering techniques.

The method of ELM was employed for training a single hidden layer feed-forward neural networks (SLFN). The ELM method was applied to determine noisy pixels of the images. Two datasets were created and tested through the ELM method, after performing the required classifications.

2.1. Employed Dataset

In this Thesis, the input volumes have been taken from the Stanford volume data archive (Levoy, 2002). The database comprises 99 slices of 256 x 256 pixels and 8-bit TIF files. Images were obtained using a CT device and collected from different positions. The CT images that were taken from the Stanford volume data archive, dimensions and bit depth per voxel of the datasets are listed in Table 2.1.

Table 2.1. Dimensions and bit depth per voxel of the datasets

Dataset	Size X	Size Y	Size Z	Depth
CTHead	256	256	99	8 bits

The original volume which is one of the noisiest slices, initial counters, and visual hull volumes are given in Figure 2.1 (a), (b) and (c) respectively.

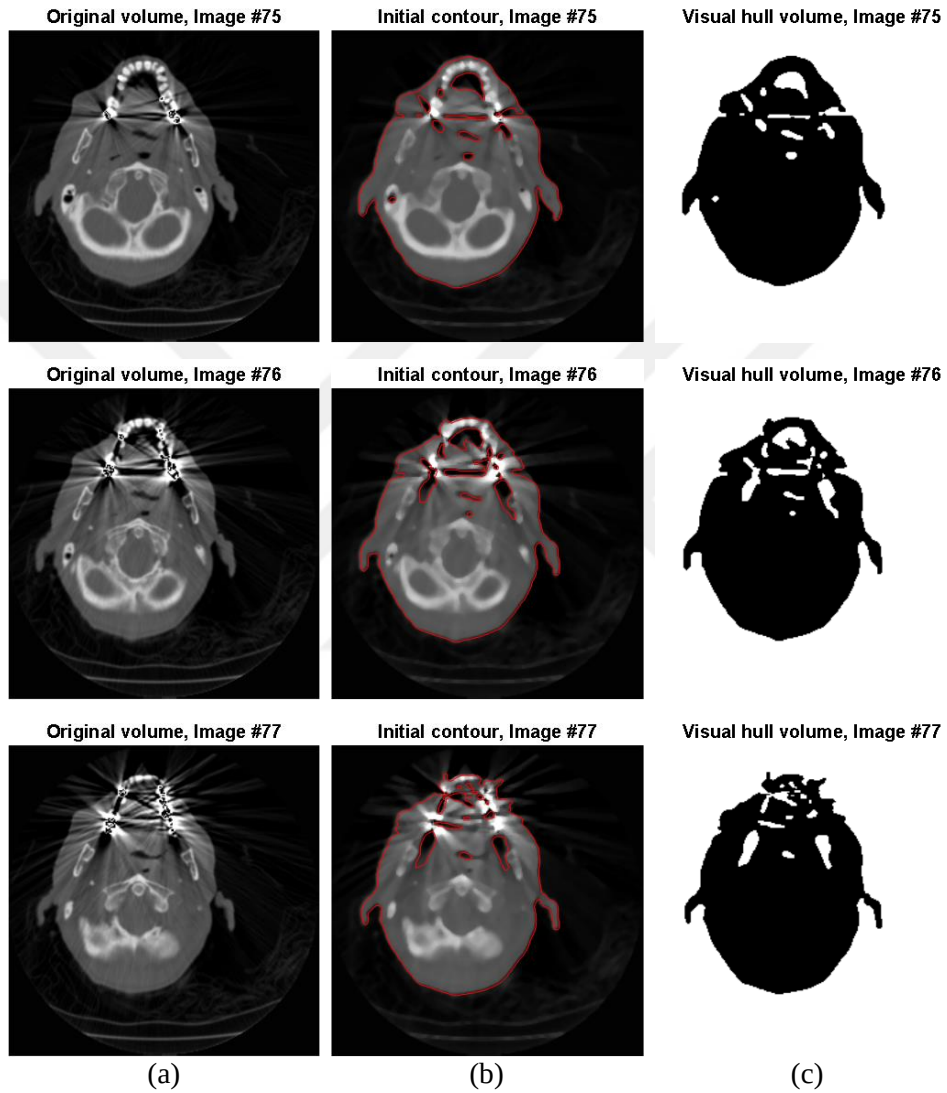


Figure 2.1. Comparison of the noisiest slices and visual hull volumes: a) Original volumes b) Initial contours c) Visual hull volumes

2.2. Traditional Methods

Image processing is predominantly used, and its usage area expands over time. Reducing or removing noise from the images is one of the most fundamental problems in image processing (Jiang et al., 2014; Azimirad and Haddadnia, 2015; Thanh et al., 2016). The first stage in the image processing stages is to obtain an image. When images are being acquired, the image becomes noisy due to various reasons. Noise is the result of external sources that degrade the image and reduce image quality. For example, television images are distorted due to atmospheric noise and a lack of image reception (Jin et al., 2016). Another reason is when scanning artwork and digitizing it, noise is added to the image because of the operations that are performed for preventing the original surfaces from being damaged. Due to such reasons, undesirable or unrealistic information is added to the images. It is impossible to get a noiseless image with today's cameras, and the cameras add a certain amount of noisy images (Cho et al., 2012).

The process of obtaining a digital image, which converts an optical image into a continuous electrical signal, is the process that first appears in digital images. Every step in the process brings natural phenomena to the fluctuations and adds a random number to the real brightness value of this pixel (Pang et al., 2016). Knowing what type of noise as it was going to happen at any step, means that it could be done with zero error. However, this is not possible in practice. As a result, denoising in the images continues to be a major problem in imaging. The image is restored to reduce or eliminate the data losses and distortions caused by noise during the formation of a scene. The apparent loss of data is noise-induced, and this deviation is the true pixel value of the noisy pixel (Meher and Singhawat, 2014).

During the acquisition phase, there is a significant reduction in the image quality during operations such as image digitization, signal amplification, and transmission due to faults in analog components or timing errors in analog-to-digital conversion (Chan et al., 2005; Morillas et al., 2008; Goossens et al., 2009; Lin et al., 2010; Zhang et al., 2014; Yuan and Li, 2015; Ananthi and Balasubramaniam, 2016).

The most important factor in denoising the images is to protect the original image information such as edges, textures (Nguyen and Chun, 2017). Image filtering, which is defined as an image processing application, applied to highlight or suppress some details in digital images, edge detection, image noise and adverse effects; is to increase the visibility of a visual image by increasing the distinction between the different physical properties included in the image (Zhang et al., 2017). With the digital filtering method, new gray shades of each pixel are calculated. Colored images are converted to a grayscale image and then filtered.

By using traditional methods in the literature, an attempt to improve the image quality by noise reduction in CT images with a large preset in the medical field (Cabello et al., 2015; Joshi et al., 2016; Djurović, 2017). Thus, various filters have been designed, that are dependent on the local characteristics of the image, which use different techniques to remove noise in digital images (Darus et al., 2016; Pang et al., 2016; Pei et al., 2016; Jayasree and Narayanan, 2017). Images must be filtered to enable image processing analysis. Filtering allows operations such as sharpening the image, extracting specific details, smoothing the image, edge sharpening, or edge detection (Zhang et al., 2017; Jiang et al., 2017). However, when filtering, all the noisy pixels on the image cannot be corrected, or the original pixel values which are not distorted remain, and the efficiency of the filtering is decreased.

2.2.1. Filtering

Noise reduction is a technique that improves the image, contributes to the removal of noise from the image, and is the first step in different processes such as object recognition (Li et al., 2016). In the filtering process, the matrix that determines the filter parameters and determines the multiplication factor of each pixel in the neighborhood of a pixel is called the kernel (Papari et al., 2017). Filtering is defined as kernel convolution.

There are linear and nonlinear filtering methods in the literature (Simon, 2010; Jain and Tyagi, 2016). Linear filters are implemented using convolution or

Fourier transforms and are available in a variety of Uniform, Triangular, Gaussian and Wiener filters (Andria et al., 2012). Nonlinear filters are filters that are used effectively in cases where linear filters are inadequate and also Median, Non-local Means (NLM) filter, Kuwahara are the various types of filters available (Khare and Nagwanshi, 2012; Djurović, 2017). Low-pass filters are commonly used to reduce noise because low-pass filters reduce the noise by taking the average. High-pass filters are used for edge detection and edge sharpening it is because they maintain edge sharpness (Singh and Singh, 2017).

In the filtering, the input image $f(i, j)$ is processed by convolution with the filter function $h(i, j)$ (Hou et al., 2016). This expression can be expressed mathematically as in Equation (2.1).

$$g(i, j) = h(i, j) \odot f(i, j) \quad (2.1)$$

Filters are used to reveal some details in the image or to remove unwanted noise. Moreover, images, which are digitally recorded meaning the devices acquire the image in error, and many losses or roughness which is caused by insufficient environmental conditions such as illumination, are attempted to be reduced using image processing filters.

Generally, filters are applied by traversing the image with a kernel of $m \times n$ (pixel) size matrix (Sharma and Tiwari, 2017). Each pixel value is multiplied by the value underneath the rotated object and divided by the sum of the elements in the filter. These operations are filtered when the image is calculated and updated for each pixel. In case of overflow for the edge pixels of the filter, the edge pixels are solved by including the edge pixel values in the process as if the next edge were present. If the denominator is zero, the denominator is set to "1". In general, filters are expressed as a 3×3 matrix. Some of the traditional filter types are listed as follows.

2.2.2. Gaussian Filter

Noise reduction in the input image is one of the most common pre-processing steps used in almost all operations related to digital image processing (Verma and Ali, 2013). When noise is destroyed, the image structure and textural information must be preserved. There are two features of an ideal filter that removes noise. To remove high-frequency noises, a filter band must be as narrow as possible to identify the edges in the frequency and space planes (Ehman et al., 2014). The best filter that provides both features is the Gaussian filter. Therefore, the Gaussian filter is one of the best used linear filters when noise is eliminated (Cabello et al., 2015).

The Gaussian filter is a linear low-pass filter and is effective at Gaussian noise reduction. As the weights of the pixels in the Gaussian kernel are in the Gaussian distribution, decreasing towards the edges. A 2D Gaussian filter has a separation feature. That is, a 2D Gaussian filter one-dimensional (1D) can be split into two filters, and the results of the filters are the same value (Gastal and Oliveira, 2011). Moreover, instead of filtering with a 2D kernel, filtering with 1D two kernels is more advantageous regarding computational cost.

A Gaussian filter is generally used to reduce the noise in signals. Destroying a noise in a signal means reducing the changes in the signal the most, or in other words, the maximum and minimum values in the signal are moderate. In this case, the 1D Gaussian filter is expressed as Equation (2.2).

$$g(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \quad (2.2)$$

The equation shows the standard deviation in the x, the variant, and the σ time domain. Gaussian filtering is also a Fourier transformation. The Gaussian filter allows an infinite transfer function to filter out a final window (scan window) in the spatial domain (Chen et al., 2013). This makes the basic problem of filtering easier

to solve. The Fourier transformation of Equation (2.2) is obtained as in Equation (2.3).

$$F\{g_\sigma(x)\} = \hat{g}_\sigma(f) = e^{-\frac{f^2}{2\sigma f^2}} \quad (2.3)$$

Equation (2.3) also represents the standard deviation in frequency f and frequency σ_f . The Equation (2.4) is also provided in the equations.

$$\sigma_x \sigma_f = (2\pi)^{-1} \quad (2.4)$$

The Fourier transformation of the Gaussian filter is again a Gaussian filter. In other words, the filter suppresses high frequencies while passing low frequencies in the signal (Shuman et al., 2013). Generally, a low-pass filter with Gaussian kernels is also used for edge detection. Negativities in the uniformly distributed filter are less common in this filter, as the weight of the center pixel in this filter is greater than that of its neighbors (Jain and Gupta, 2015). Filtering can also be performed in a vertical axis with the result first horizontally followed by (Günther et al., 2015).

The 2D Gaussian function is obtained by the product of two 1D Gaussian functions, and it is given in the Equation (2.5).

$$g(x, y, \sigma_x, \sigma_y) = \left[\frac{1}{\sqrt{2\pi} \sigma_x} e^{-\frac{x^2}{2\sigma_x^2}} \right] \left[\frac{1}{\sqrt{2\pi} \sigma_y} e^{-\frac{y^2}{2\sigma_y^2}} \right] \quad (2.5)$$

Where x is the distance from the center of the horizontal axis and y is the distance from the center of the vertical axis, this means distance σ_x is the standard deviation in the x direction and σ_y is the standard deviation in the y direction. When σ_x and σ_y are taken equal, the 2D Gaussian function is expressed in Equation (2.6).

$$g(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (2.6)$$

The user determines the σ (standard deviation) value for the variance and a constant value is taken for the whole pixel in the image (Mazzoleni et al., 2015). A large selection of the variance value increases the amount of noise removal but also causes blurring of the image and destruction of the edges. Minimizing the variance value reduces the amount of noise reduction and increases the preservation of edges and detail (Cabello et al., 2015). With the 2D filter, the edges with high-frequency components can be eliminated while the noise in the image is reduced. This is a disadvantage of the Gaussian filter. The size of the Gaussian kernel is generally chosen to be 3x3, 5x5, 7x7. The size of the kernel can be increased as desired. However, this increases the calculation time excessively and reduces the performance of the filter. Generally, 3x3 and 5x5 kernel sizes are used in image processing algorithms. In applications, the user first determines the kernel size and the filter variance σ , and then the input image and the Gaussian kernel are convoluted to output image is obtained. Filter variance is the most important influence on the performance of the Gaussian image filter. Filtering with small variance values is not very effective on the input image, but filtering with large variance values causes blurring in the image and a loss of detail.

Figure 2.2 gives an example of a 2D Gaussian function with a standard deviation of 0,2 and x and y of [-1,1]. Herein, x is the distance from the origin to the horizontal axis, y is the distance from the origin to the vertical axis, and σ is the standard deviation of the Gaussian distribution (Cabello et al., 2017).

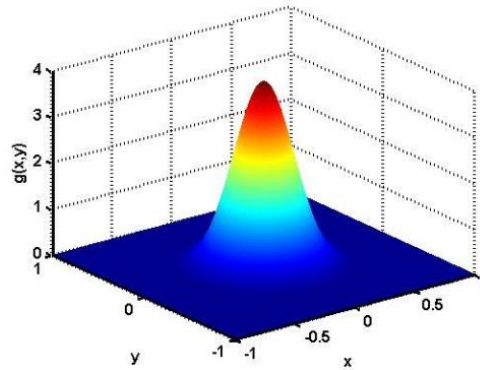


Figure 2.2. 2D Gaussian function

When the σ variance value is greater than 2.5, the Gaussian filter behaves like an average filter, and when the variance value is less than 0.3, the filter does not affect the image (Çelik et al., 2015). Namely, σ should be chosen between 0.3 and 2.5. The graphs of the Gaussian kernels produced for different variance values as represented in Figure 2.3.

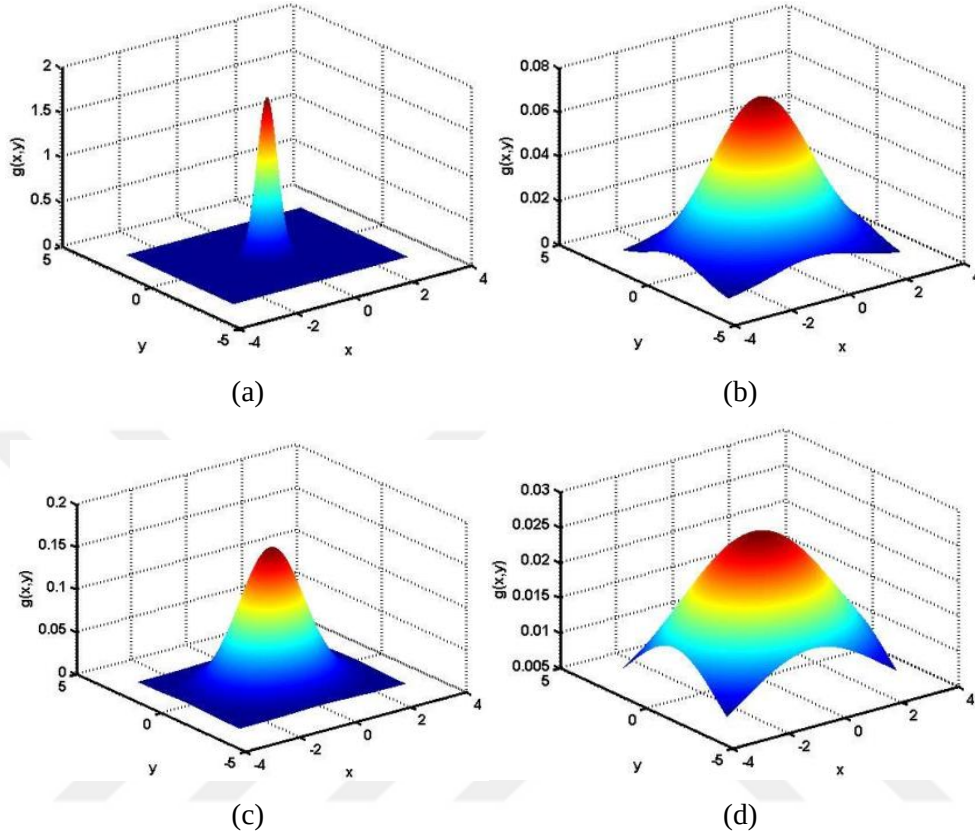


Figure 2.3. Graphs of Gaussian kernels produced for different variance values
a) $\sigma = 0,3$ b) $\sigma = 1$ c) $\sigma = 1,5$ d) $\sigma = 2,5$

2.2.3. Non-Local Means Filter

The NLM filter is based on the assumption that the pixels in a noisy image are predicted with the help of weighted averages of neighboring pixels (Zachiu et al., 2017). In this way, the details of the image and small objects can be detected (Ambrosanio et al., 2017). This process is applied to all the pixels on the image by using Equation (2.7).

$$NLMF(X_i) = \sum_{x_j \in SW} w(X_i, X_j) \cdot \mu(X_j) \quad (2.7)$$

In Equation 7, X_i and X_j are the i^{th} and j^{th} pixel values in X image, respectively (Buades et al., 2011). X_j is limited to a specific search window (SW) to reduce the calculation time. $\mu(X_j)$ is the intensity value at the j^{th} pixel. $w(X_i, X_j)$, which forms the basis of the NLM filter, represents the weight function between the i and j pixels. The weight function is calculated as follows (Equation 2.8).

$$w(X_i, X_j) = \frac{1}{C(X)} \sum_{\delta \in P} e^{\frac{G_a |\mu(X_i+\delta) - \mu(X_j+\delta)|^2}{h^2}} \quad (2.8)$$

In Equation (2.8), G_a is the Gaussian kernel and h is the filtering parameter. This parameter controls the effectiveness of the filter and is proportional to the noise level in the image. The δ symbol refers to the patch that accepts the i^{th} and j^{th} pixels as the center pixel. $C(X)$ is the normalization factor and is calculated by the following equation (Equation 2.9).

$$C(X) = \sum_{X_j \in SW} w(X_i, X_j) \quad (2.9)$$

$C(X)$ which is given in the Equation equals to the sum of the i^{th} center pixel and the weight functions of all the pixels in the search window.

The selection of the parameters of the NLM filters directly affects the filter performance (Yang et al., 2015). The patch (P) and SW dimensions must be selected appropriately. A wider SW will both increase the processing load and cause it to be involved in the process at remote pixels that will not contribute to the cleaning process. Likewise, if the patch size is selected small enough, it will not be able to use sufficient information, or if it is selected large, it will lose the feature of protecting details by using excess information.

2.2.4. Kuwahara Filter

Kuwahara is a non-linear smoothing filter used for adaptive noise reduction in image processing (Djurović, 2017). This filter reduces noise in the image and maintains the sharpness of the edges. Filters that do not change the location and sharpness of the edges, such as the Kuwahara filter, are defined as edge preserving filters (Bartyzel, 2016). In this method, four regions are formed around a center pixel (see Figure 2.4).

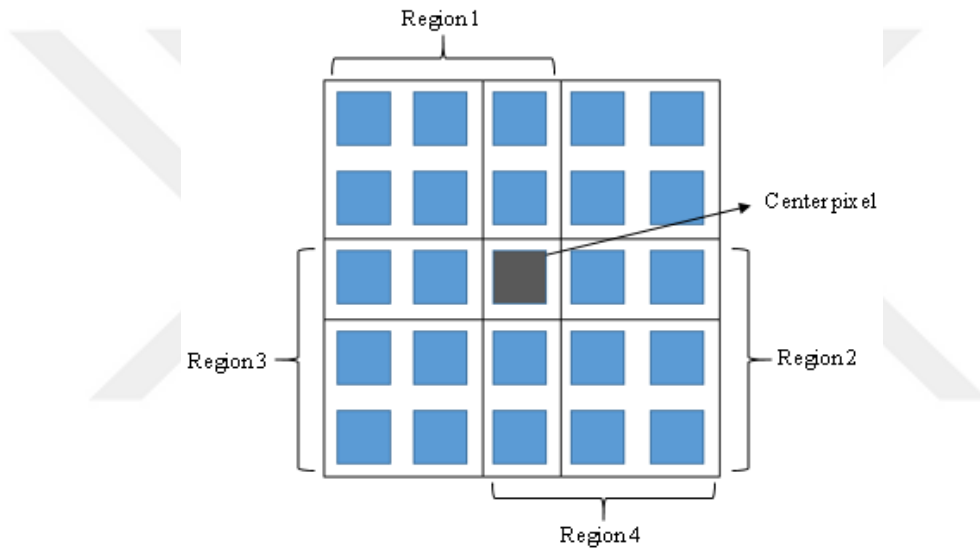


Figure 2.4. Example of a 5x5 Kuwahara filter containing 3x3 sampled regions

The average and variance of the brightness value of each region are calculated. The center value of the center pixel is determined as the average of the brightness value of the lowest value variance (Biswas and Ghoshal, 2017). Using a window as in Figure 2.5, the Kuwahara filter is divided into four square regions, namely a, b, c, d. The pixel in the middle and the column belongs to more than one region.

a	a	a/b	b	b
a	a	a/b	b	b
a/c	a/c	a/b/ c/d	b/d	b/d
c	c	c/d	d	d
c	c	c/d	d	d

Figure 2.5. A window used by Kuwahara filter

2.2.5. Thresholding

This is a method used to convert input image to binary image. The binary image is defined as a black and white image (Lai and Rosin, 2014). It is used for different purposes, such as morphological operators, reducing noise on an image or specifying an object (Murthy and Sadashivappa, 2014). Depending on the type of thresholding applied to the input image, the pixels are updated in black or white according to the given threshold value (Gonzalez et al., 2004). A threshold is a border value used when converting a gray-scale raster image to a black and white format (Dhara et al., 2017). For example; when a threshold value of 180 for a gray-scale raster object scanned in 256 colors is specified, one will be assigned for each cell larger than 180, and zero for other cells.

A threshold filters the pixel values of the source view to very large or very small values. It is mostly used to remove noise from the images. There are several threshold types available (Hareva et al., 2016).

Binary Type: If the pixel on the source image is larger than the threshold value, it is assigned to the parameter value given as the maximum value (*maxVal*). $f(x, y)$ is the source image and $g(x, y)$ is the target image (Equation 2.10).

$$g(x,y) = \begin{cases} \text{maxal} & , \text{ if } f(x,y) > \text{thresh} \\ 0, & \text{otherwise} \end{cases} \quad (2.10)$$

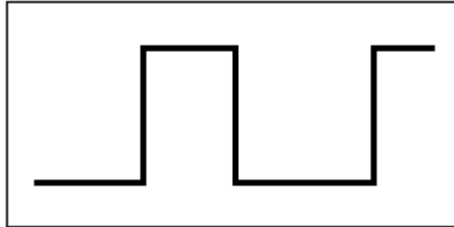


Figure 2.6. Binary type

Binary Inverted Type: If the pixel on the source image is smaller than the threshold value, it is assigned to the parameter value given as the maximum value (Equation 2.11).

$$g(x,y) = \begin{cases} 0 & , \text{ if } f(x,y) > \text{thresh} \\ \text{maxVal}, & \text{otherwise} \end{cases} \quad (2.11)$$

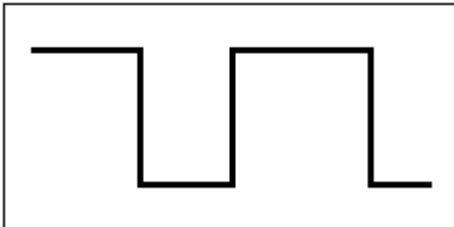


Figure 2.7. Binary inverted type

To Zero Type: If the pixel on the source image is larger than the threshold value, the pixel value will be preserved; if it is smaller, the pixel will be assigned as black (Equation 2.12).

$$g(x,y) = \begin{cases} f(x,y) & , \text{ if } f(x,y) > \text{thresh} \\ 0, & \text{otherwise} \end{cases} \quad (2.12)$$

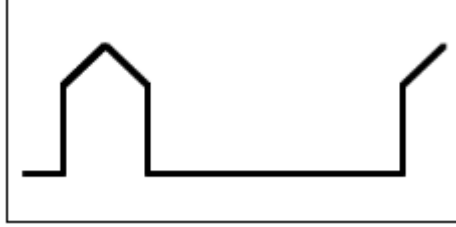


Figure 2.8. Zero type

To Zero Inverted Type: If the pixel on the source image is smaller than the threshold value, the pixel value will be preserved. If it is bigger, the pixel will be assigned as black (Equation 2.13).

$$g(x,y) = \begin{cases} 0, & \text{if } f(x,y) > thresh \\ f(x,y), & \text{otherwise} \end{cases} \quad (2.13)$$



Figure 2.9. Zero inverted type

Truncate Type: If the pixel on the source image is larger than the threshold value, the pixel will be assigned as black; if it is small, the pixel value will be preserved (Equation 2.14).

$$g(x,y) = \begin{cases} threshold, & \text{if } f(x,y) > thresh \\ f(x,y), & \text{otherwise} \end{cases} \quad (2.14)$$



Figure 2.10. Truncate type

2.3. Feature Extraction

In this stage, first noisy pixels were determined. Following this, the pixel values around the targeted noisy pixel are located. Figure 2.11 shows the pixel values around the targeted noisy pixel.

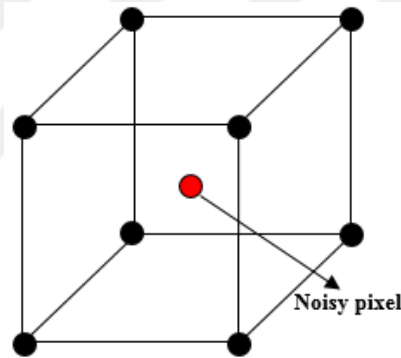


Figure 2.11. Illustration of a noisy pixel as a voxel cell

The classification was done for the entire system as presented in Table 2.2 and Figure 2.12, taking into consideration neighborhood relations for each noisy pixel.

Table 2.2. Classification of noisy pixels

f_{n-1}	f_n	f_{n+1}	Classification
9 members	8 members	9 members	1: Noisy Pixel
			0: Noiseless Pixel

Each noisy pixel has eight neighborhoods in its frame (f_n) and nine neighborhoods in its previous frame (f_{n-1}), and nine in the next frame (f_{n+1}) (Figure 2.12). For each pixel value in the reference image, 26 connected pixel values were examined (eight neighborhoods in its frame, nine neighborhoods in its previous frame, and nine neighborhoods in the next frame). The average weights of the noisy pixels were calculated through this model utilizing the similarity of pixel neighborhoods.

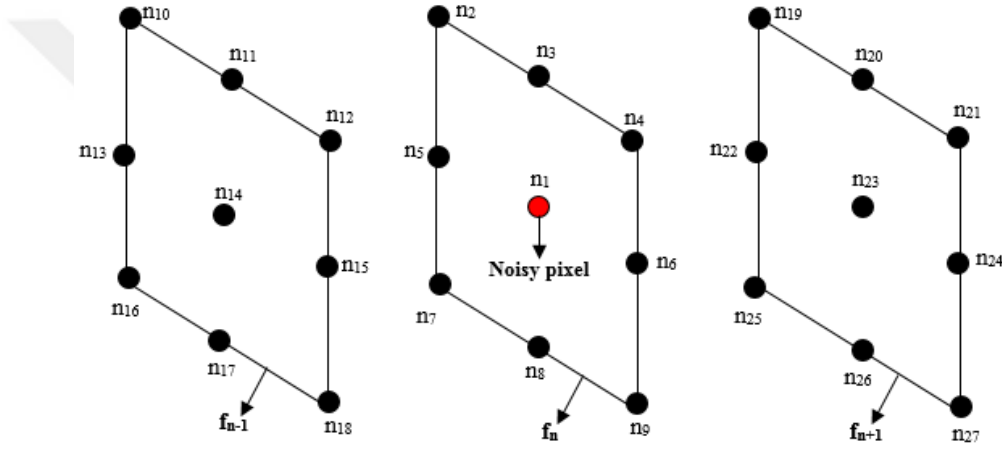


Figure 2.12. Classification of noisy pixels

In order to create a dataset, noisy pixels have to be determined. Equation (2.15) represents the frame number (f_n) and the pixel values (x, y) for a noisy pixel sample (I).

$$I(f_n; x, y) = \text{noise} \quad (2.15)$$

To generate a dataset in the classification phase, each pixel determined as noisy by the ELM system was assigned a value of 1, and a value of 0 was assigned to a pixel that were noiseless (Table 2.2). By performing these classifications, two datasets were created. During the first stage of operations of the designed system,

the dataset was created following each pixel belonging to the image being determined to either be noisy or not. To detect noisy pixels, the created dataset was trained by the ELM method and compared with other images. In the last stage, all the trained datasets were tested using cross-validation method, and the overall performance values of the system were measured (Figure 2.13).

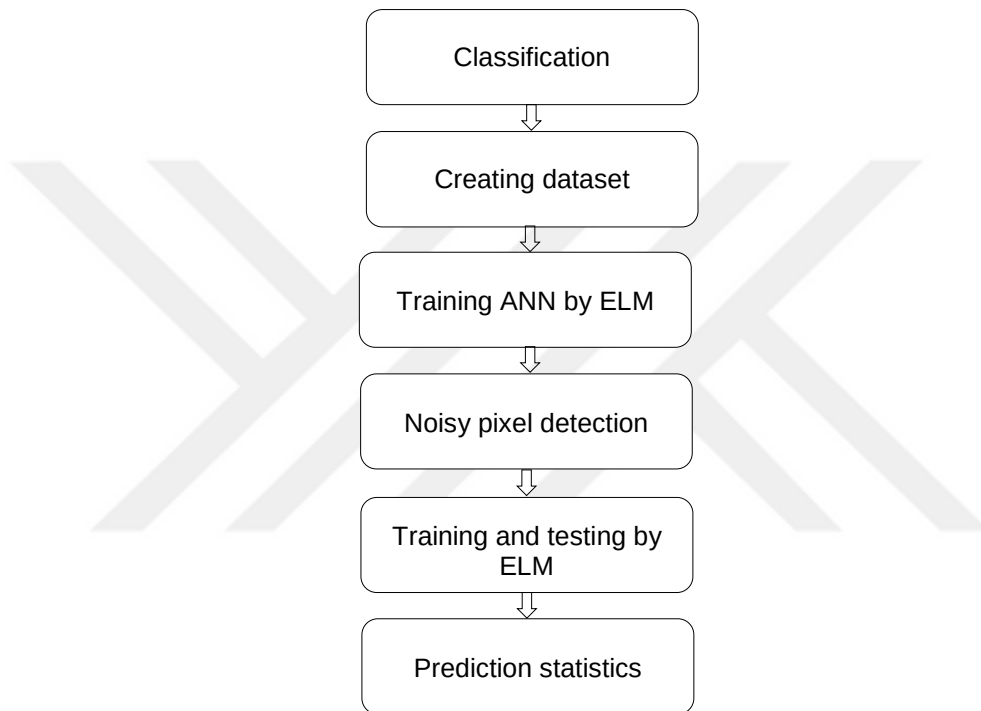


Figure 2.13. Filtering 2D medical images by ELM

2.4. Classification

2.4.1. Extreme Learning Machines

The ELM method maintains the SLFN to become popular in recent times and provides the resolution of the smallest norm and least squares method at a very low runtime for the solution of non-linear problems (Cao et al., 2015).

Huang et al. (2006) have proposed the learning algorithm, which was called as ELM in their study. This algorithm was proposed for SLFN. These neural

networks randomly select the hidden nodes and determine the output weights analytically. This algorithm tends to theoretically provide a good generalization performance (Ertuğrul and Kaya, 2014). It does this performance with an extremely fast learning capability. Experimental results have shown that this algorithm provides an appropriate generalization performance. For SLFN, it is stated that they can learn thousands of times faster than known algorithms.

ELM (Luo, 2014) used for the SLFN neural network model is primarily proposed as SLFN in conducted studies (Huang et al., 2006). In later studies, it was developed as a generalized SLFN that is not the one hidden layer in the neural network (Huang, 2007). The weight values of the neurons in the input layer neuron generated by ELM and the threshold values of the neurons in the hidden layer are randomly generated, and the weight values of the neurons in the output layer are measured analytically (Tang et al., 2015). Hardlimit, Gaussian, and Sigmoid, activation functions are used in the hidden layer while the linear function was used at the output layer (Huang, 2014). Artificial neural networks (ANN) has traditionally been able to recalculate the weights of these models. However, Huang et al. (2006) proposed a new method of calculating the weight of the model in an analytically at once method. They proved that the solution to be obtained by this method is unique. The name of this method is named as ELM, and it has been studied in detail by Huang et al. since 2006. It is possible to use the ELM model in each of the above-listed fields since the model is trained faster and is based on ANN.

For ELM, there is a need for an activation function that will shape the output of the model as well as the ANN, and this function has to be specified by the user. Different types of activation functions are available. Formulas for different activation functions are given in Table 2.3. Moreover, the user can also develop a different activation function, and the user can use it in the ELM method. In the current study, the activation functions in the MATLAB platform (Neural Networks Toolbox) are used.

Table 2.3. Activation Functions used in the ELM Method

Number	Activation Function	Equation
1	Sigmoid	$f(x) = \frac{1}{(1+e^{-n})}$
2	Elliot Sigmoid	$\alpha = \frac{0.5 * n}{(1+abs(n))} + 0.5$
3	Hard Limit	$\alpha = \begin{cases} 1, n \geq 0 \\ 0, n < 0 \end{cases}$
4	Radial basis	$\alpha = \exp(-n^2)$
5	Normalized Radial Basis	$\alpha = \frac{\exp(-n^2)}{\sum \exp(-n^2)}$
6	Sine	$\alpha = \sin(n)$
7	Cosine	$\alpha = \cos(n)$
8	Triangular Based	$\alpha = \begin{cases} 1 - abs(n), if -1 \leq n \leq 1 \\ 0, else \end{cases}$
9	Linear	$\alpha = n$
10	Linear Saturated	$\begin{cases} 0, if n \leq 0 \\ n, 0 < n < 1 \\ 1, 1 \leq n \end{cases}$
11	Positive Linear	$\alpha = \begin{cases} n, if n \geq 0 \\ 0, if n < 0 \end{cases}$

ELM was an ability of higher generalization. As it can be evidently noted, there are no repeated steps in the training process (Ertuğrul and Kaya, 2014). In many applications, good performances with high learning speeds can be attained (Tang et al., 2016). In addition to this, it may be considered an advantage to specify fewer parameters. In ANN, it is necessary for the user to decide on the parameters related to training. In the ELM method, training takes place analytically. However, it is a disadvantage to decide which activation function should be used and also to decide on the number of neurons in the middle layer.

ELM is similar to ANN, which has one hidden layer. For this reason, up to a certain level, the working principle of ELM and ANN are similar to each other. However, with ELM, the weights (w) in the hidden layer are randomly assigned, and these values are not changed in the later stages of training. By contrast, the weights (β) between the hidden layer and the output layer are determined analytically and quickly by means of a linear model (Hoang et al., 2007; Sun et al., 2014). The basic ELM model is SLFN based model, which is one hidden layer, and the difference with ANN explained as above. In the general SLFN model, there is a known data for input and output values. The structure of the single hidden layer ANN has been visualized in Figure 2.14.

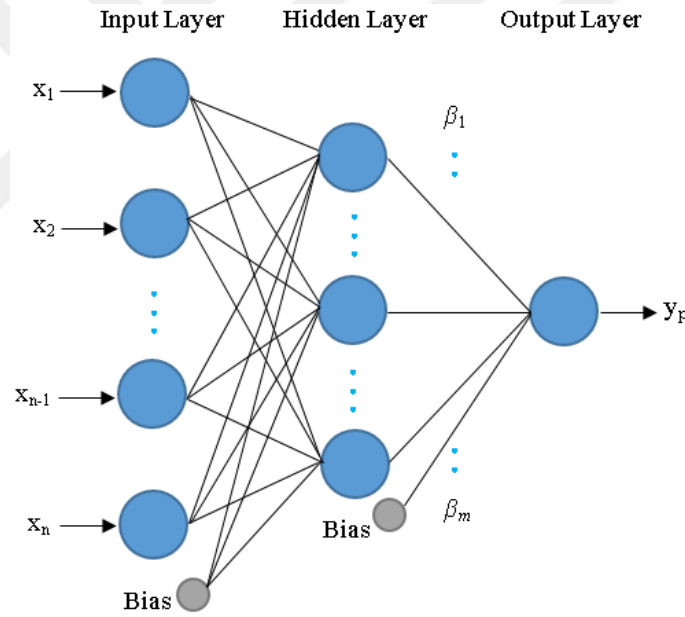


Figure 2.14. Architecture of ELM

For a standard model as in Figure 2.14, $\{(x_i, y_i)\}_{i=1}^N$ pairs containing N training samples show samples in $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in \mathbb{R}^n$ n -dimensional space while $y_i = [y_{i1}, y_{i2}, \dots, y_{im}]^T \in \mathbb{R}^m$ shows samples m possible output

nodes. A single hidden layer ELM containing $\tilde{N}$ hidden layer node is mathematically modeled as in Equation (2.16).

$$\sum_{i=1}^{\tilde{N}} \beta_i g_i(x_j) = \sum_{i=1}^L \beta_i g(w_i \cdot x_j + b_i) = o_j, j = 1, 2, \dots, N \quad (2.16)$$

The $w_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T \in \mathbb{R}^n$ vector represents the weight values between the input layer and the i^{th} hidden layer, while the $g(\cdot)$ in this expression indicates an activation function. $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{im}]^T \in \mathbb{R}^m$ is the weight value between the i^{th} hidden layer node and o_j output layer nodes. The value shown as b_i is the bias value of the i^{th} hidden layer node. As shown in the example Equation (2.17) with $\tilde{N}$ hidden layer nodes and $g(\cdot)$ activation function, β_i , w_i and b_i can be converged with a zero error average (Cao et al., 2015). Accordingly, the equation in the matrix format shown in Equation (2.18) can be written.

$$\sum_{j=1}^{\tilde{N}} \|o_j - y_j\| = 0 \quad (2.17)$$

$$H\beta = Y \quad (2.18)$$

H in this equation represents the hidden layer output values. According to the β_i , w_i and b_i parameters, Equation (2.19) can be expressed in matrix form as shown below.

$$H = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \cdots & g(w_{\tilde{N}} \cdot x_1 + b_{\tilde{N}}) \\ \vdots & \ddots & \vdots \\ g(w_1 \cdot x_N + b_1) & \cdots & g(w_{\tilde{N}} \cdot x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}} \quad (2.19)$$

The weight values between the β , hidden layer and the output layer and the labels of the Y samples are shown in Equation (2.20). According to the ELM method,

this minimizes the training error while also minimizing the output norm (Huang et al., 2006; Huang et al., 2012).

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix}_{\tilde{N} \times m} \quad \text{and} \quad Y = \begin{bmatrix} y_1^T \\ \vdots \\ y_N^T \end{bmatrix}_{N \times m} \quad (2.20)$$

According to Moore-Penrose's generalized matrix inversion theorem (Ullah et al., 2014), in the system of an equation of $H\beta = Y$, the notion of a non-square matrix in $n \times m$ dimensions is as in Equation (2.21) which provides the solution of the smallest norm and least squares.

$$\beta^* = H^\dagger Y \quad (2.21)$$

Moore-Penrose may use different methods to obtain a generalized matrix inverse. One of these methods is the orthogonal projection method. According to the ridge regression theory (Hoerl, 2000), adding a positive value to the diagonal of the HH^T or H^TH matrices ensures that the system produces more stable results and has higher generalized performance (Huang et al., 2012). C is a constant value, and I is the variable that expresses the unit matrix. Thus, the expression in Equation (2.21) can be expanded as in Equation (2.22).

$$\beta^* = H^T (\frac{I}{C} + HH^T)^{-1} Y \quad (2.22)$$

After the weight values β^* between the hidden layer and the output layer are obtained, the hidden layer output values for the test data X_t are found by the calculation in Equation (2.23).

$$h(x_t) = g(w^t x_t + b) \quad (2.23)$$

In order to complete the classification process, the β^* calculated using the training set as shown in Equation (2.24) is used.

$$f(x_t) = h(x_t)\beta^* = h(x_t)H^T(\frac{1}{C} + HH^T)^{-1}Y \quad (2.24)$$

When the training of the ELM has been initialized, the input weight and bias values are initialized with random values selected in the interval [0, 1]. Thus, the ELM functions very fast by minimizing the training error and the output weights with a single matrix inversion without the need to fix any parameters.

2.4.2. Support Vector Machine

Support vector machines (SVM) is a trained classification technique based on statistical learning theory (Peng, 2010). SVM is a machine learning algorithm that tries to generalize and estimate on new data by learning on training data sets that do not assume any knowledge about the distribution. Input variables and outputs in training sets are matched. By means of matches, decision functions, which are separated from each other by different classes, are obtained (Wang et al., 2011). New data input variables are classified by the decision function. In general, the working principle of the SVM is to determine the decision boundaries that divide the data belonging to the two classes in a most appropriate way. The most basic classification problem for SVM is the classification of a "two-class" data set that can be separated "linearly" (Tian et al., 2014). To solve this problem, SVM tries to determine the best separator plane which makes the best difference between the two classes and which has the maximum boundary between the classes. The best separating plane maximizes the distances of the separating plots of the data of each class. The learning data closest to the hyperplanes constitutes support vectors that define the boundary between two classes (Shao et al., 2014).

Kernel function selection and parameter optimization play an important role in the implementation of SVM. The SVM generates an n-dimensional hyperplane that optimally divides the data into two categories. The SVM models are closely related to ANN. SVM using a sigmoid kernel function has a two-layer, feed-forward ANN (Huang et al., 2012).

When non-linear separability is considered, the training samples can not be linearly separated in the original input space. In such cases, SVM transforms to the high dimensional feature space, which can be easily classified linearly from the original input space by means of the nonlinear mapping function. Thus, instead of finding the product values of all values repeatedly by using kernel functions, it is directly substituted in the kernel function and the value of the attribute space is found. At this point, there is no possibility of dealing with a very high-dimensional quality space. Another advantage of the core functions is that it is much easier to calculate the values for the other examples after the function is set up and values are found in the training stage (Amari and Wu, 1999). SVM has four core functions that are widely used. These functions are Linear, Polynomial, Sigmoid and Radial Basis functions.

2.4.3. Multi-Layer Feed-Forward Neural Networks

Multi-layer feed-forward neural networks (MLP-FNN) are networks in which the signal is transmitted unidirectional from the network entrance to the exit (Huang et al., 2004). Cells in a layer can only take the output of the previous layer as an input. The activation function used in MLP-FNN determines the output of the cell to produce this input by processing the net entry into the cell (Zhang et al., 2007). The activation function is usually chosen to be a non-linear function. "Nonlinear" which is one characteristic of the ANN, comes from the nonlinear nature of activation functions. Another point to note when selecting the activation function is that the derivative of the function is easily computable. In the feedback networks, since the derivation of the activation function is also used, a derivative function is

chosen so that the calculation does not slow down. In the most widely used "multi-layer perceptron" model today, Sigmoid function is generally used as the activation function (Huang et al., 2004). The MLP-FNN is divided into two networks.

A. Single-Layer MLP-FNN

In general, a single cell cannot perform the desired input-output function. Cells with the same properties except connection weights are brought together to form layers. In the simplest form, a layered neural network input layer can be considered as the layer in which input signals are applied to the network. Signals in the input layer are connected to the output layer by weights. Such a structure is called a single layer ANN (Huang et al., 2000). In this structure, information processing is straightforward. The input layer is not counted as a layer because no calculation is made.

B. Multi-Layer MLP-FNN

Such neural networks can be distinguished by the presence of one or more hidden layers (Glorot and Bengio, 2010). The hidden layer creates a relationship between the input layer and the output layer. When the size of the input layer increases, the math processing capacity of the hidden layer at a higher level is more important.

2.5. Activation Functions

ELM consists of three separate layers, namely, the input layer, hidden layer, and output layer. Activation functions such as Sigmoid, Sine, Radial Basis, Hard-Limit, and Triangular Basis are used in the hidden layer. A linear function is used in the output layer, (Akın and Ceylan, 2015).

The activation functions determine the output of the cell to produce a response to the input by processing the net entry into the cell (Sibi et al., 2013). The correct selection of the activation function significantly affects the performance of

the network. The value derived from the activation function is given as the output of the artificial neural network, or it can be used in the network again. Although each cell has more than one entry, there is only one output. This output can be linked to the desired number of cells (Lecun et al., 2015).

The activation function is usually chosen to be a nonlinear function (Zhang and Suganthan, 2016). Another point to note when selecting the activation function is that the derivative of the function is easily computable. Since the derivation of the activation function is also used in feedback networks, a simple computational function of the derivative is chosen so that the computation does not slow down (Adigun and Kosko, 2017). In today's most widely used multi-layer sensor model, the Sigmoid function is generally used as an activation function (Hajduk, 2017).

According to the activation function used, the output value is usually between $[-1, 1]$ or $[0, 1]$ (Sibi et al., 2013). This is usually a non-linear function. The use of non-linear activation functions allows ANN to be applied to complex and very diverse problems.

Sigmoid, Sinus, Hard Limit, Triangular Basis, and Radial Basis activation functions were used in this study.

Sigmoid: The Sigmoid activation function is a continuous and derivable function (Wu et al., 2014). It is the most frequently used function in ANN applications due to its non-linearity. This function generates a value between 0 and 1 for each of the input values. The mathematical expression of the sigmoid function is as shown in Equation (2.25) (Iliev et al., 2017).

$$f(x) = \frac{1}{(1+e^{-x})} \quad (2.25)$$

The name of the Sigmoid function comes from the letter S (Sigma), which is similar to the function drawn by cartesian space. This drawing is shown in Figure 2.15.

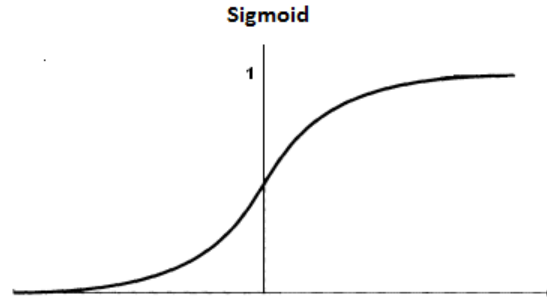


Figure 2.15. Sigmoid function

Sinus: It is used in situations where the events thought to be learned are appropriate for sinus function (Yang and Wu, 2016). The mathematical expression of the Sinus function is as shown in Equation (2.26).

$$f(x) = \sin(x) \quad (2.26)$$

The graph of sinus function is shown in Figure 2.16.

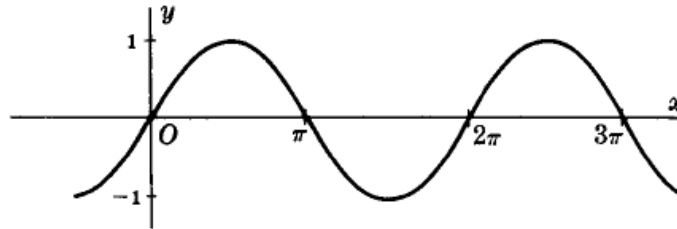


Figure 2.16. Sinus function

Hard Limit: This function is used to obtain discrete results according to the values of the input patterns (Singh et al., 2015). In other words, the input gives either +1 or -1 (Figure 2.17). There is no other possibility. This allows a precise limit to be taken (Equation 2.27).

$$\alpha = \begin{cases} 1, n \geq 0 \\ -1, n < 0 \end{cases} \quad (2.27)$$

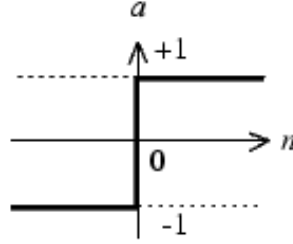


Figure 2.17. Hard limit function

Triangular Basis: The Tribas function is a neural transfer function (Pandey and Singh, 2016). It calculates the output value of a layer's net input (Equation 2.28).

$$\alpha = \begin{cases} 1 - \text{abs}(n), & \text{if } -1 \leq n \leq 1 \\ 0, & \text{else} \end{cases} \quad (2.28)$$

n in the equation; If the value is between $[-1, 1]$, the absolute value is taken by the $1 - \text{abs}(n)$ formula. If n is less than -1 or greater than 1 , the result is 0 (Figure 2.18).

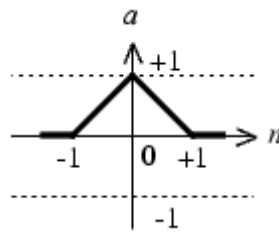


Figure 2.18. Triangular function

Radial Basis: In ANN, the center point function is the weight function, and the position and the width are the activation function that can be adjusted in the

learning process (Deng and Lin, 2017). The most typical radial basis function is the Gaussian function. This function is used in MATLAB with the `radbas(n)` equation (Equation 2.29). An example of a Radial-Based Gaussian activation function is shown in Figure 2.19.

$$a = e^{-n^2} \quad (2.29)$$

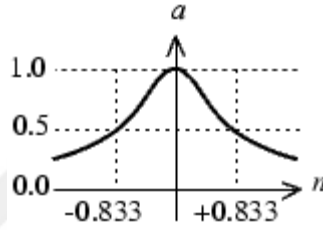


Figure 2.19. Radial basis function

2.6. Error Metrics

The effects on images of image processing algorithms can be evaluated in two ways, subjective and objective (Biswas et al., 2018; Ghadiyaram and Bovik, 2016). Subjective evaluation only refers to the comparison and evaluation of images with the human eye. This method does not give independent results because it has changed personally. Measurement methods based on specific mathematical models are used for objective evaluation. This method is more suitable for evaluating the quality of image and the success of the used algorithm since the results are the same for everyone.

After filtering the images that are exposed to the noise with the used algorithm, the measurement of the similarity to the original image is done by the performance criteria which are quantitative methods (Oza and Joshi, 2016). These pioneer performance criteria are MSE, PSNR and Structural Similarity Index (SSIM). With these methods, the effects of different image processing algorithms on

the same image are evaluated and systematically compared to determine which is more successful.

2.6.1. MSE

MSE is a metric measurement unit that allows to measure how similar two pixel values (Biswas et al., 2018). The image is used to measure the similarity of the original image with the filtered image in the process. The MSE gives the average of the sum of the squares of the differences of the actual image and the entire pixel values of the filtered image. The error measures how different the filtered view is from the original image and is defined by Equation (2.30) (Ali, 2017).

$$MSE = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (I(x, y) - I'(x, y))^2 \quad (2.30)$$

In this formula:

I : The data matrix of the original image,

I' : Data matrix of the filtered image,

M : Represents the number of rows of pixels in the image while x represents the index of the row,

N : Represents the number of columns of pixels in the image while y represents the index of the column.

2.6.2. PSNR

PSNR refers to the ratio between maximum signal value and the signal quality representing value (Zhang et al., 2017). Because many signals have a very wide dynamic range, the PSNR is usually expressed logarithmically. The mathematical expression of PSNR is defined by Equation (2.31) (Zhou et al., 2012).

$$PSNR = 20 \log_{10} \left(\frac{L}{\sqrt{MSE}} \right) \quad (2.31)$$

Where MSE is the mean square error. L indicates the maximum color value of the pixels in the original image. High PSNR means that the filtered image is closer to the original image. For this, the MSE error must be as small as possible. If it is desired to calculate the MSE error of two identical images, the result will be 0 (zero) and the result will be undefined because Equation (2.31) will be divided by 0 (zero). This is a disadvantage of the PSNR.

2.6.3. SSIM

SSIM is based on comparing the brightness, contrast, and structure of the three entities of the two images (Garg and Khandelwal, 2018). SSIM measures the similarity ratio between two images in a way that gives more consistent results with human perception than traditional techniques such as average square error (Oza and Joshi, 2016). For example, blurred images are perceived poorly by the human eye and they are not measured in the MSE method, but they are observed in the SSIM metric measurements. Due to the relationship of SSIM to human perception, it finds application areas for analysis of compressed video images, image quality and video analysis.

In this method, the luminance (L), contrast (c), and structure (s) properties are obtained independently. The SSIM index for x and y images is obtained by the following equation (Equation 2.32) (Rehman and Wang, 2011).

$$SSIM(x, y) = f(I(x, y), c(x, y), s(x, y)) \quad (2.32)$$

Where $I(x, y)$ is the brightness comparison function and is obtained by Equation (2.33) (Channappayya et al., 2008).

$$I(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \quad (2.33)$$

In the equation, $c_1 = (K_1 L)^2$, K_1 is a small constant $K_1 \ll 1$, and L is the pixel distribution measure. The contrast comparison function is obtained by Equation (2.34).

$$c(x, y) = \frac{2\sigma_x\sigma_y + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \quad (2.34)$$

In the equation, $c_2 = (K_2 L)^2$, K_2 is a small constant value $K_2 \ll 1$ and L is the pixel distribution measure. $s(x, y)$ is obtained by the structure comparison function Equation (2.35).

$$s(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \quad (2.35)$$

Finally, the SSIM index is obtained by the following equation (Equation 2.36).

$$SSIM(x, y) = [I(x, y)^\alpha \cdot c(x, y)^\beta \cdot s(x, y)^\gamma] \quad (2.36)$$

In the Equation, $\alpha > 0$, $\beta > 0$ and $\gamma > 0$

If $\alpha = \beta = \gamma = 1$ and $c_3 = c^2/2$, it is calculated as defined in the SSIM Equation (2.37).

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \quad (2.37)$$

In Equation (2.37); x and y are compared images. μ_x (Equation 2.38), σ_x (Equation 2.39) and σ_{xy} (Equation 2.40) indicate the pixel density average, standard deviation and covariance of the estimated image, respectively.

$$\mu_x = \frac{1}{N} \sum_{i=1}^N x_i \quad (2.38)$$

$$\sigma_x = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \mu_x)^2} \quad (2.39)$$

$$\sigma_{xy} = \frac{1}{N-1} \sum_{i=1}^N (x_i - \mu_x)(y_i - \mu_y) \quad (2.40)$$





3. RESULTS

3.1. Obtained noise detection results by ELM

ELM method was used to determine noisy pixels. By making classifications, dataset was created, and tested by the ELM. First, the dataset is divided into five equal parts (Figure 3.1), and subsequently, four of them were considered as training data and one of them was utilized as test data. The training and classification process was carried out five times through cross validation, whereby different dataset was used for each time. As a result of this process, the accuracy values obtained each fold was averaged, and the accuracy of the overall system was calculated.

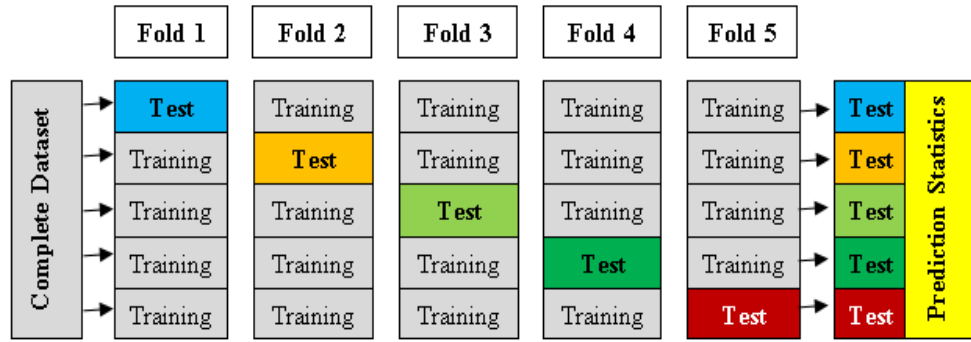


Figure 3.1. Estimated statistics with k-fold cross-validation (k=5)

Equation (3.1) was applied for the performance values of the designed system. The test performance values of the system are calculated by dividing the number of correctly classified pixels by the total number of pixels.

$$Test \text{ accuracy } (\%) = \frac{\text{correctly classified pixels}}{\text{total number of pixels}} \times 100 \quad (3.1)$$

Training and test accuracy values of ELM network classifier are given in Table 3.1, and Table 3.2, respectively. In the testing process, a leave-one-out cross

validation method was used to test overall system accuracy. Each image that created the dataset was included in the test set alternately.

The optimum success rate of the system was calculated using the ELM method by varying the number of neurons in the hidden layer during training, and testing. Sigmoid, Sine, Hard Limit, Triangular Basis, and Radial Basis were considered as the activation function. The number of neurons in the hidden layer was considered between 10 and 1500. Therefore, the number of neurons in the most appropriate hidden layer was varied from 10 to 1500 with different neuron steps. Following the achievement of the optimum success rate, the optimum number of neurons was determined at the point where the performance of the system decreased. It was observed that the best success rate of the system was attained through the Sigmoid activation function. The success rate of the training was between 75.38 – 88.23% (Table 3.1) while test success rate of the system was between 75.37 - 87.20% (Table 3.2). The highest success rate was achieved in the hidden layer of 250 neurons. It was observed that successful results were obtained with detecting noisy pixels when the results of the ELM method were examined.

A low MSE value means less error. When the MSE value decreases, the error rate in the image also decreases. There is an inverse ratio between MSE and PSNR values. Namely, a low value of MSE implies a high value of PSNR. Moreover, it can be clearly viewed from the MSE and PSNR results presented in Table 3.3 and Table 3.4 that the most successful performance value is reached with the number of hidden neurons at 250. The best result of the system was noted with the MSE value of 0.148 and the PSNR value of 56.46.

Table 3.1. Training accuracy (%) values of ELM network classifier

Number of Neurons in the Hidden Layer	Activation Function				
	Sigmoid	Sine	Triangular Basis	Radial Basis	Hard Limit
10	75.38	63.41	74.98	74.68	75.18
25	77.23	63.83	74.93	74.59	76.37
50	79.73	63.93	75.22	75.98	78.29
75	81.34	64.18	76.34	76.31	80.19
100	84.64	66.47	77.79	77.64	83.26
150	86.52	66.52	78.13	78.61	84.67
200	87.32	67.84	78.20	79.28	85.60
250	87.56	68.22	78.91	80.10	85.73
500	87.82	68.78	79.02	80.17	86.18
750	88.04	68.83	79.57	80.94	86.31
1000	88.16	69.00	79.52	80.96	86.46
1500	88.23	69.15	79.65	81.01	86.55

Table 3.2. Test accuracy (%) values of ELM network classifier

Number of Neurons in the Hidden Layer	Activation Function				
	Sigmoid	Sine	Triangular Basis	Radial Basis	Hard Limit
10	75.37	63.42	74.98	74.68	75.17
25	77.23	63.80	74.92	74.57	76.36
50	79.70	63.88	75.22	75.98	78.28
75	81.32	64.05	76.33	76.28	80.16
100	84.53	65.87	77.65	77.46	83.15
150	86.35	65.52	77.82	78.32	84.49
200	87.18	66.28	78.41	79.67	85.39
250	87.20	66.08	77.98	79.18	85.52
500	85.59	65.75	77.36	77.32	83.85
750	84.53	65.87	77.65	77.46	83.15
1000	83.72	64.80	77.39	75.54	82.16
1500	82.19	64.32	75.77	75.81	80.24

Table 3.3. MSE values of ELM network classifier

Number of Neurons in the Hidden Layer	Activation Function				
	Sigmoid	Sine	Triangular Basis	Radial Basis	Hard Limit
10	0.266	0.386	0.270	0.273	0.268
25	0.248	0.382	0.271	0.274	0.256
50	0.223	0.381	0.268	0.260	0.237
75	0.207	0.380	0.257	0.257	0.218
100	0.175	0.361	0.243	0.245	0.189
150	0.156	0.365	0.242	0.237	0.175
200	0.148	0.357	0.236	0.223	0.166
250	0.148	0.359	0.240	0.228	0.165
500	0.164	0.363	0.246	0.247	0.182
750	0.175	0.361	0.243	0.245	0.189
1000	0.183	0.372	0.246	0.265	0.198
1500	0.198	0.377	0.262	0.262	0.218

Table 3.4. PSNR (dB) values of ELM network classifier

Number of Neurons in the Hidden Layer	Activation Function				
	Sigmoid	Sine	Triangular Basis	Radial Basis	Hard Limit
10	53.911	52.301	53.848	53.800	53.879
25	54.225	52.345	53.838	53.783	54.076
50	54.681	52.353	53.886	54.011	54.414
75	55.010	52.373	54.071	54.062	54.772
100	55.742	52.586	54.301	54.267	55.411
150	56.221	52.544	54.331	54.420	55.733
200	56.458	52.635	54.438	54.677	55.961
250	56.460	52.610	54.360	54.580	55.990
500	56.013	52.572	54.249	54.242	55.576
750	55.742	52.586	54.301	54.267	55.411
1000	55.550	52.460	54.250	53.940	55.190
1500	55.200	52.400	53.980	53.980	54.790

The noise pixel detection of the system was also compared with the other images in the CT database, and the noisy pixels were accurately marked. The noises obtained from the images of different segments are displayed in Figure 3.2. The figure present that the ELM method is successful in detecting intense noisy pixels on the outer of images with low noise. However, as seen in the images, noisy pixel detection was successfully accomplished in images with noisy pixels both on the inner and outer sides.

In the classification stage of noisy pixels, a feature vector is constructed by considering a previous (f_{n-1}) and a following (f_{n+1}) frame for each sample frame (f_n). The pixel values of the sample images used in the classification stage have been extracted from the training data and used only in the test phase. The addresses of the detected noisy pixels were marked with a red dot.

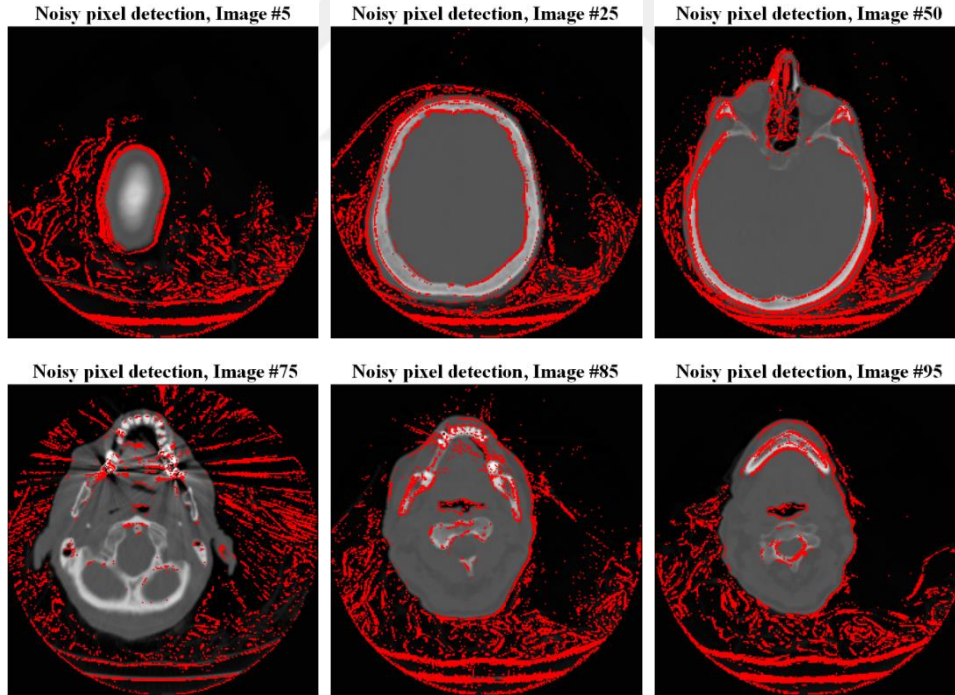


Figure 3.2. Noisy pixel detection with ELM method

A 3D surface model was constructed utilizing 2D medical image data, which has been obtained from different locations in the CT device. Figure 3.3 illustrates a noisy 3D surface model rendering from the CT images in the database. As observed in the 3D surface model, the head of the cadaver appears to be covered in a material similar to the piece of cloth, the back is covered together with an object similar to pillow, and the teeth are kept together by iron-like objects.

Figure 3.4 shows the histogram of the 3D surface model. The histogram shows the pixel values from 0 to 255 in the x-axis, while the y-axis shows the total number of pixels in the 3D view of the entire image in the database (99 x 255 x 255).

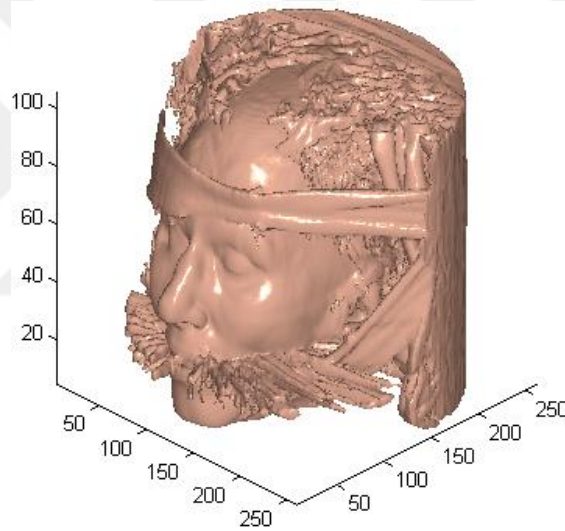


Figure 3.3. Noisy 3D surface model

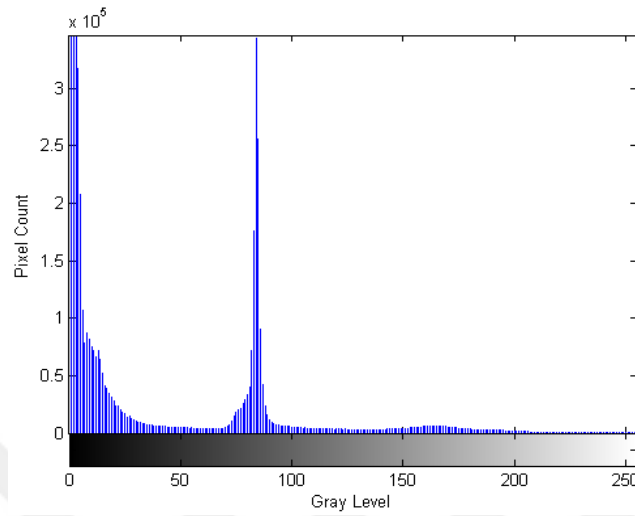


Figure 3.4. The histogram of noisy 3D surface model

The new pixel value which will replace the noisy pixels, have been detected by the ELM method has been estimated with neighborhood principles. The new pixel values were found by taking the average of the denoised pixel values around the noisy pixel values. Finally, a 3D surface model was performed from the denoised images (Figure 3.5).

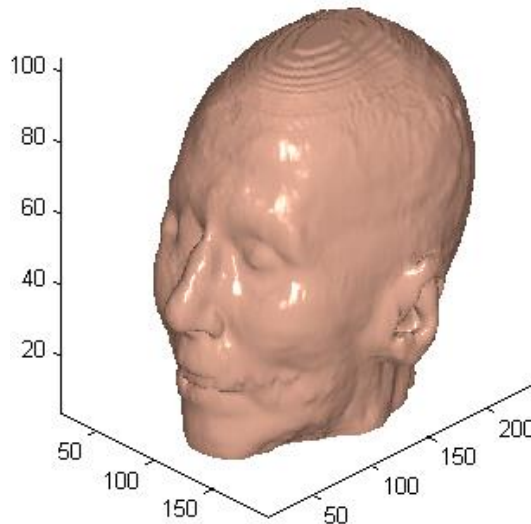


Figure 3.5. Denoised 3D surface model based on ELM method

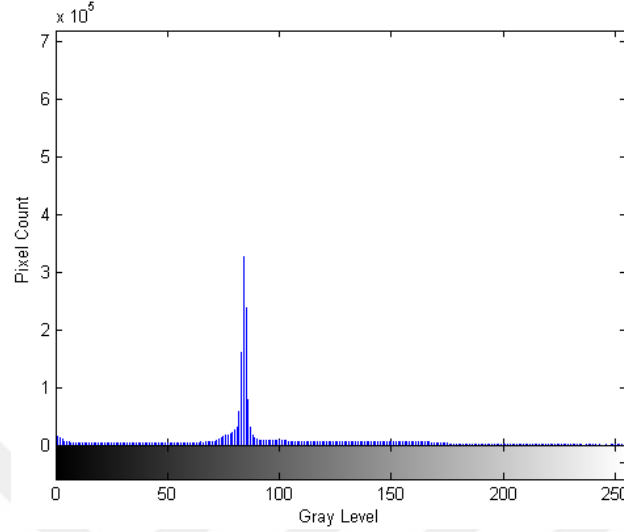


Figure 3.6. The histogram of denoised 3D surface model based on ELM method

As can be seen from the histogram in Figure 3.4, the intensity values of the pixels did not show a normal distribution due to noise. After denoising, the pixel values showed a normal distribution (Figure 3.6).

The SSIM values were examined between noisy and denoised images (Table 3.5). Similarity values between images were found for a frame (f_n) referenced from noisy original images by considering the previous (f_{n-1}) and the following (f_{n+1}) frames. SSIM values were re-calculated after the images were cleaned from noise. After denoising the images, it was seen that the value of SSIM, which is in the range of 0-1, was closed to 1. The same values of the SSIM between two images mean that they are individually similar.

Table 3.5. SSIM values between noisy and denoised images

Reference Frame	Noisy Images – SSIM index		Denoised Images – SSIM index	
f_n	f_{n-1}	f_{n+1}	f_{n-1}	f_{n+1}
n=5	0.902	0.883	0.956	0.948
n=10	0.844	0.843	0.928	0.927
n=15	0.852	0.854	0.925	0.922
n=20	0.873	0.888	0.940	0.944
n=25	0.930	0.935	0.961	0.963
n=30	0.945	0.952	0.972	0.973
n=35	0.967	0.966	0.981	0.982
n=40	0.955	0.956	0.976	0.978
n=45	0.961	0.958	0.977	0.976
n=50	0.958	0.956	0.978	0.973
n=55	0.920	0.913	0.948	0.947
n=60	0.905	0.873	0.940	0.934
n=65	0.898	0.897	0.936	0.929
n=70	0.874	0.879	0.921	0.922
n=75	0.784	0.741	0.888	0.890
n=80	0.835	0.780	0.917	0.926
n=85	0.874	0.916	0.954	0.967
n=90	0.925	0.926	0.977	0.979
n=95	0.926	0.925	0.977	0.975

3.2. Results of the Traditional Filters

Some segmentation processes were performed to eliminate the noises in the data. Additionally, filtering algorithms were applied to obtain the required contour areas. The studies were carried out in order to specify the thresholding values over the existing data. Gaussian, Kuwahara and NLM filters have been tested for the most intense 2-D noisy images.

The Gaussian filters use images with a Gaussian-smoothing kernel specified by sigma. The sigma values range between 0.5 (default) and 2. The sigma variant is used for the standard deviation of the Gaussian kernel. The results for different the sigma values 0.5, and 1.5, of the Gaussian filter are presented in Figure 3.7. As the value of sigma increases, the required locations on the image becomes blurred.

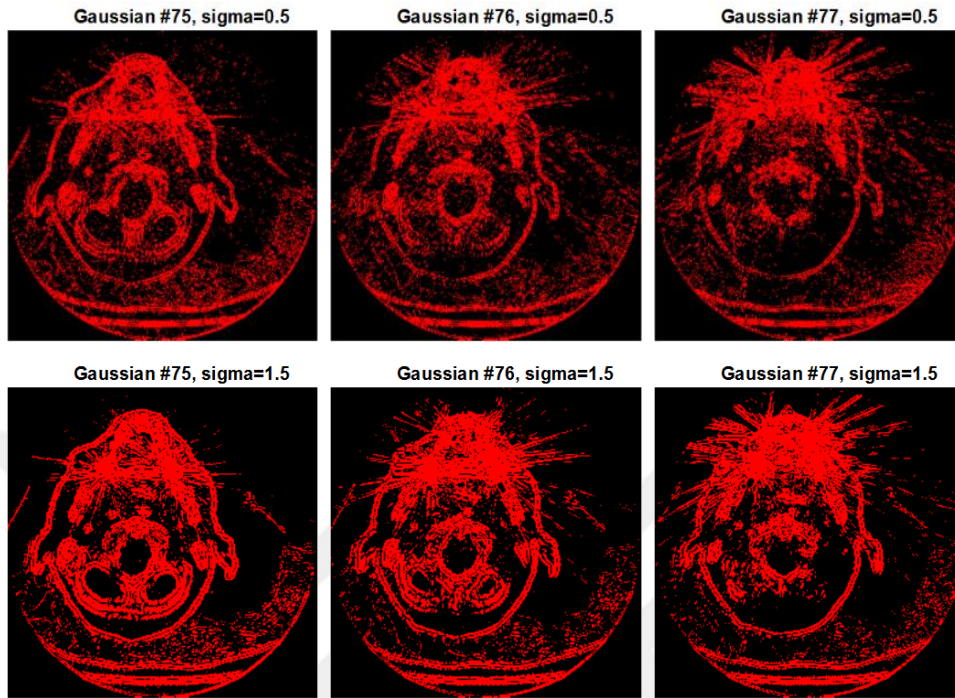


Figure 3.7. The results for different sigma values of the Gaussian filter

Gauss filter is used to perform 3D surface models with different sigma values and then the histogram of the images is extracted. The 3D surface model of the Gaussian filter for sigma value of 0.5 is shown in Figure 3.8 and its histogram is shown in Figure 3.9.

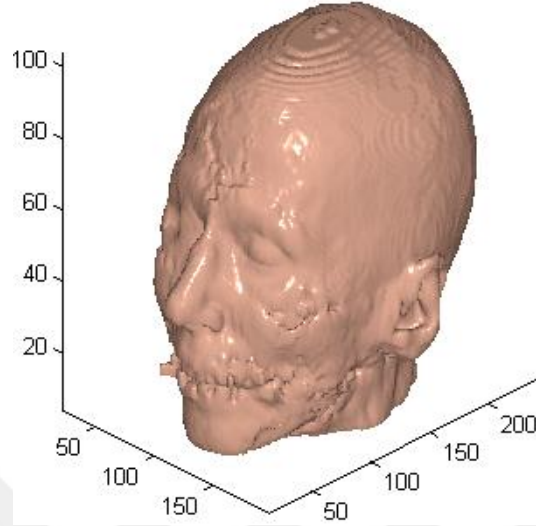


Figure 3.8. 3D surface model using Gaussian filter (sigma=0.5)

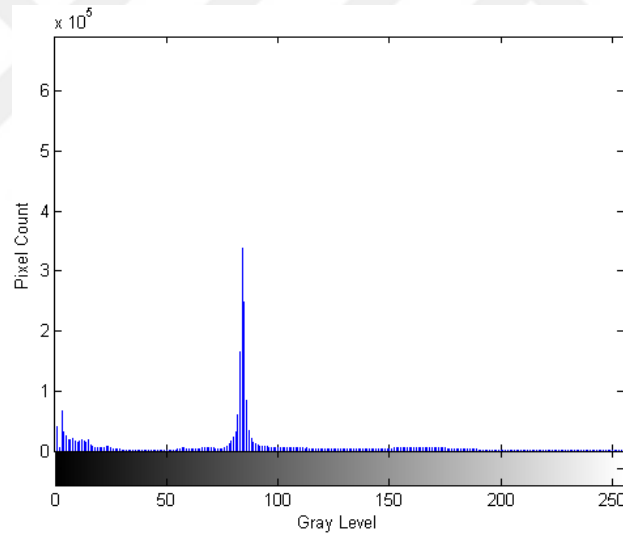


Figure 3.9. The histogram of 3D surface model using Gaussian filter (sigma=0.5)

The 3D surface model of the Gaussian filter for sigma value of 1.5 is shown in Figure 3.10 and its histogram is shown in Figure 3.11.

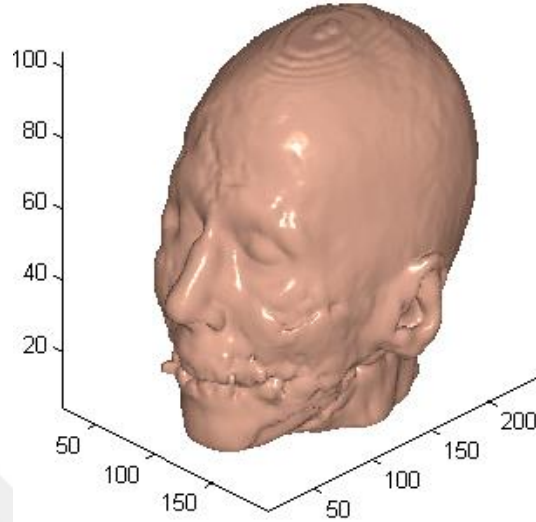


Figure 3.10. 3D surface model using Gaussian filter (sigma=1.5)

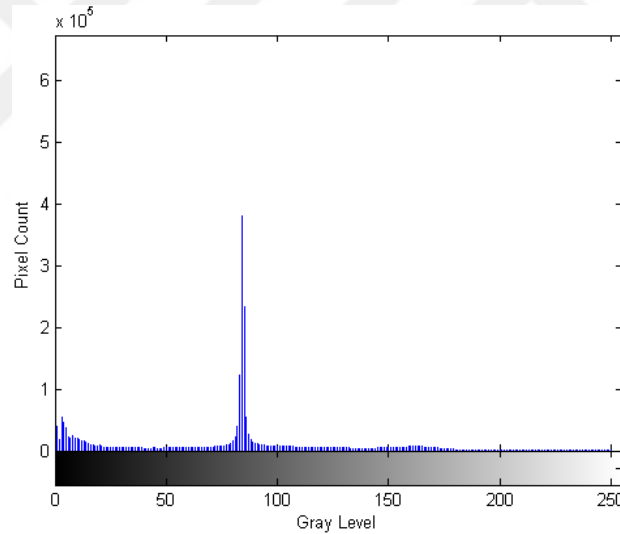


Figure 3.11. The histogram of 3D surface model using Gaussian filter (sigma=1.5)

Principle NLM filter is as follows: A local pixel region surrounding a given pixel, is compared to the pixel patches in the neighborhood. The central pixels of the patches are averaged, depending on the quadratic pixel distance between the patches. The strength of the filter is considered an adaptively varying coefficient that of the NLMF. The filter strength default value is approximately 0.05. The result for

different strength values of 0.05 and 0.2 of the NLMF has been displayed in Figure 3.12. As the strength value increases, areas that fall outside the noisy region become blurred.

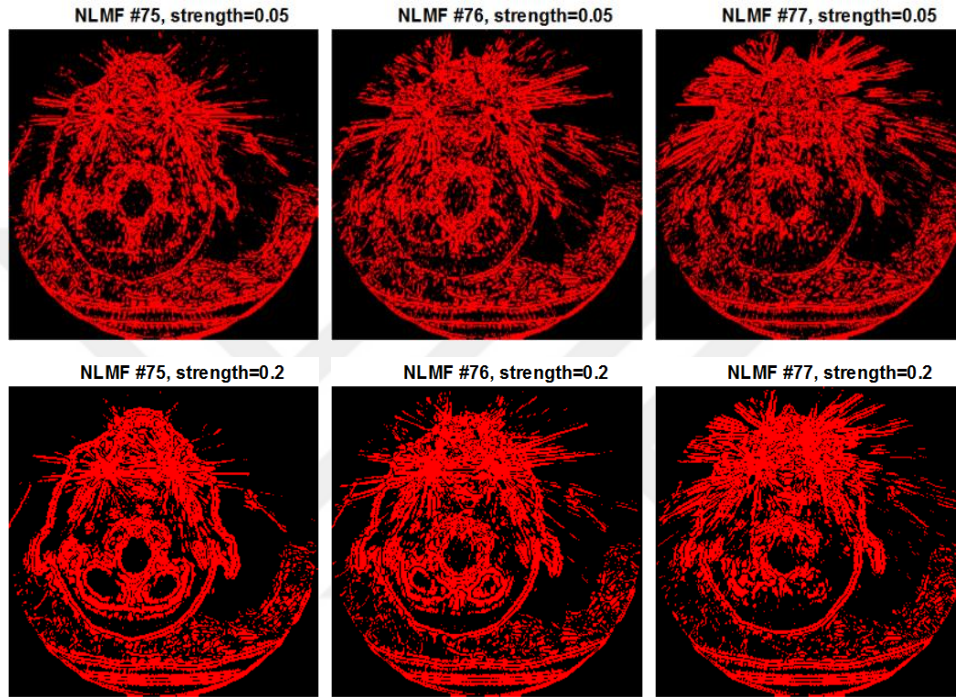


Figure 3.12. The results for different strength values of the NLMF

NLMF is used to perform 3D surface models with different filter strength values and then the histogram of the images is extracted. The 3D surface model of the NLMF for filter strength value of 0.05 is shown in Figure 3.13 and its histogram is shown in Figure 3.14.

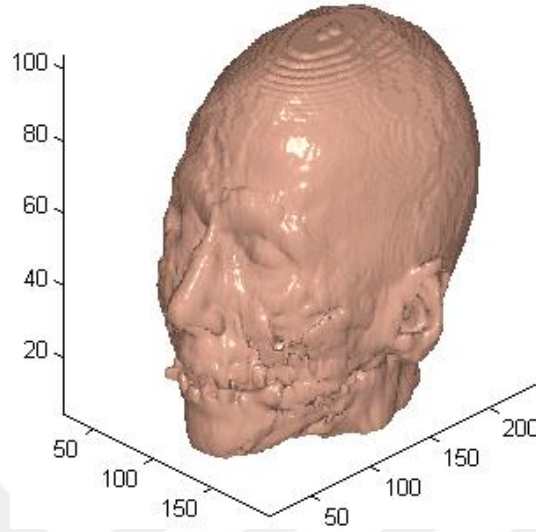


Figure 3.13. 3D surface model using NLMF (strength=0.05)

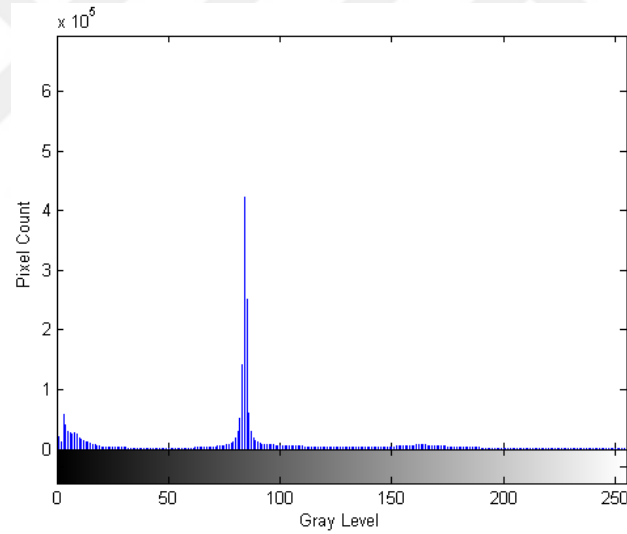


Figure 3.14. The histogram of 3D surface model using NLMF (strength=0.05)

The 3D surface model of the NLMF for filter strength value of 0.2 is shown in Figure 3.15 and its histogram is shown in Figure 3.16.

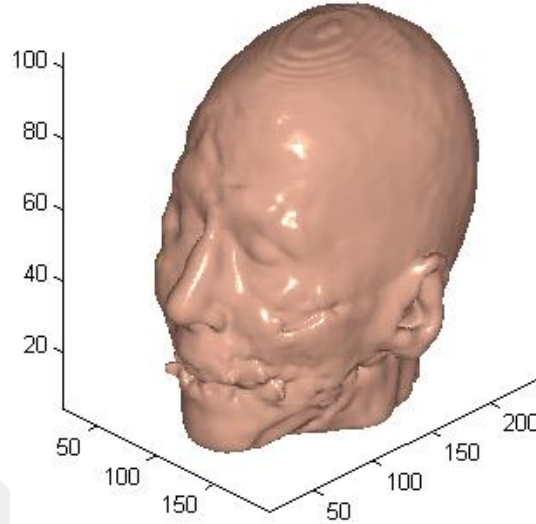


Figure 3.15. 3D surface model using NLMF (strength=0.2)

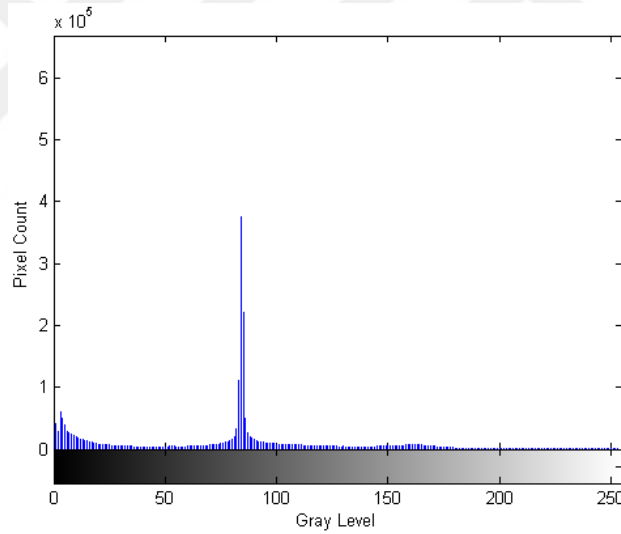


Figure 3.16. The histogram of 3D surface model using NLMF (strength=0.2)

The Kuwahara filter uses a floating windows size approach to access each pixel in the image. The size of the window is preselected and can be changed depending on the desired level of blur. The default value for window size is 5. The window size in the filter is compared for different images with values 3 and 5. The results of different window size values of the filter is provided in Figure 3.17. As the

window size grows, the noise in the images decreases, and as a result of these areas the exterior of the noisy region lost its appearance.

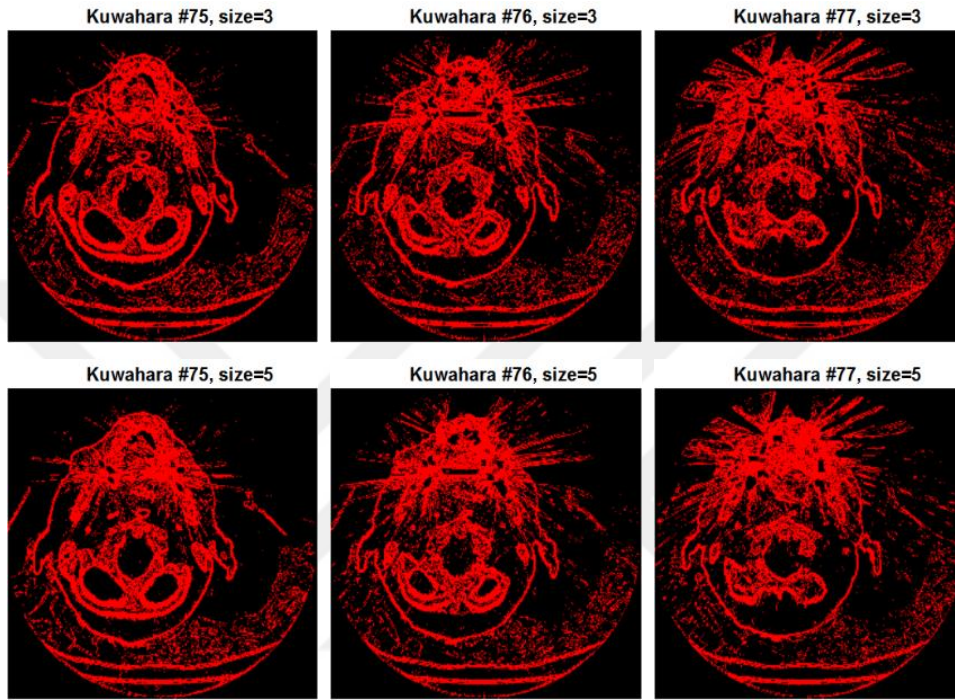


Figure 3.17. The results of different window size values of the Kuwahara filter

Kuwahara filter is used to perform 3D surface models with different filter size values and then the histogram of the images is extracted. The 3D surface model of the Kuwahara filter for filter size value of 3 is shown in Figure 3.18 and its histogram is shown in Figure 3.19.

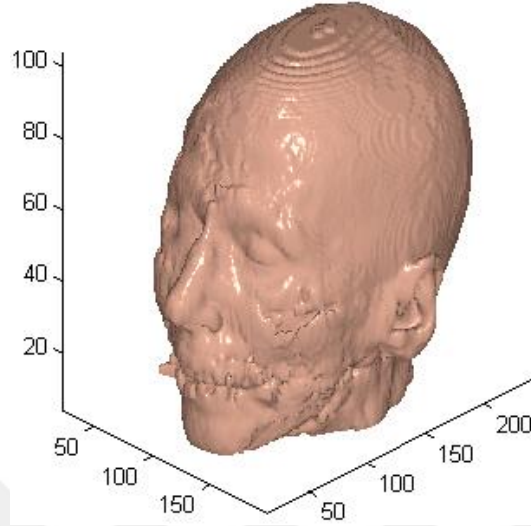


Figure 3.18. 3D surface model using Kuwahara filter (size=3)

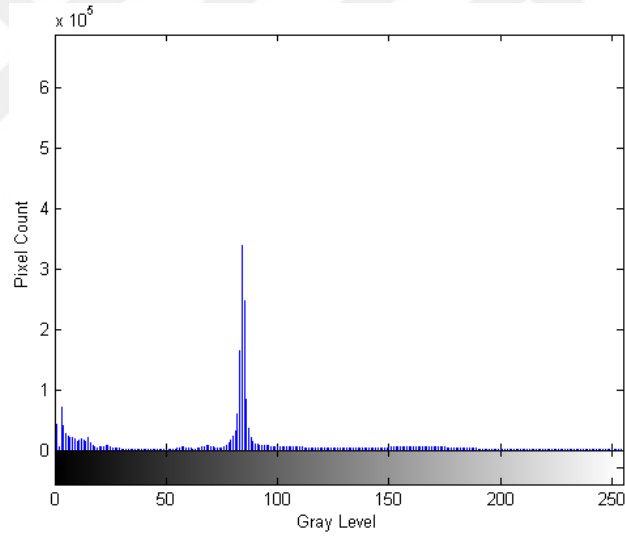


Figure 3.19. The histogram of 3D surface model using Kuwahara filter (size=3)

The 3D surface model of the Kuwahara filter for filter size value of 5 is shown in Figure 3.20 and its histogram is shown in Figure 3.21.

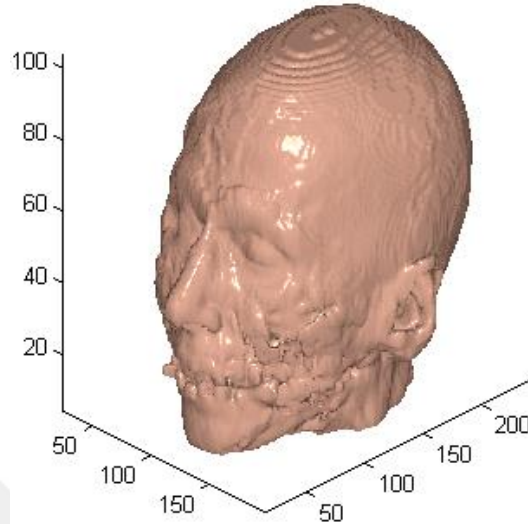


Figure 3.20. 3D surface model using Kuwahara filter (size=5)

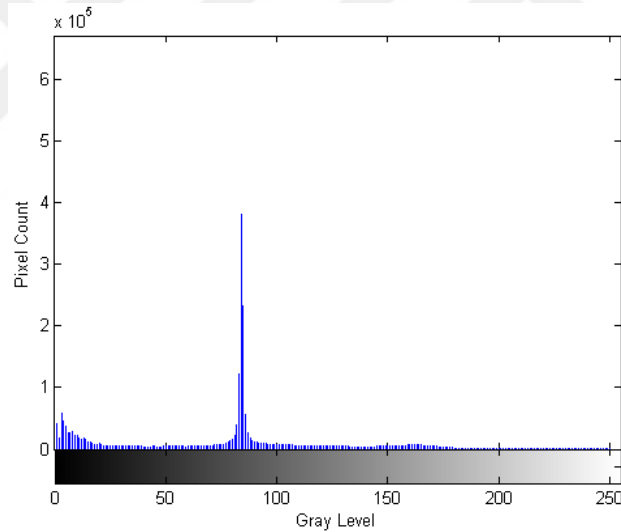


Figure 3.21. The histogram of 3D surface model using Kuwahara filter (size=5)

3.3. Results of the Threshold

The thresholding method is also studied in order to understand how detection of pixels (tissue pixels, noisy pixels) works on CT images according to the value of threshold. The intensity value of each pixel ranges between 0, and 1. The value of 0 is assigned to white pixel, and 1 is assigned to black pixel. The noisy pixels in images

are close white color. Therefore, the threshold is used to identify the pixels that are close to noisy pixel values but are actually far from noisy ones. In order to compute automatic threshold values, the data set will be created by using adaptive approach. In case of not detecting noisy pixels by threshold, these noisy pixels are manually marked. The results for different threshold values are shown in Figure 3.22.

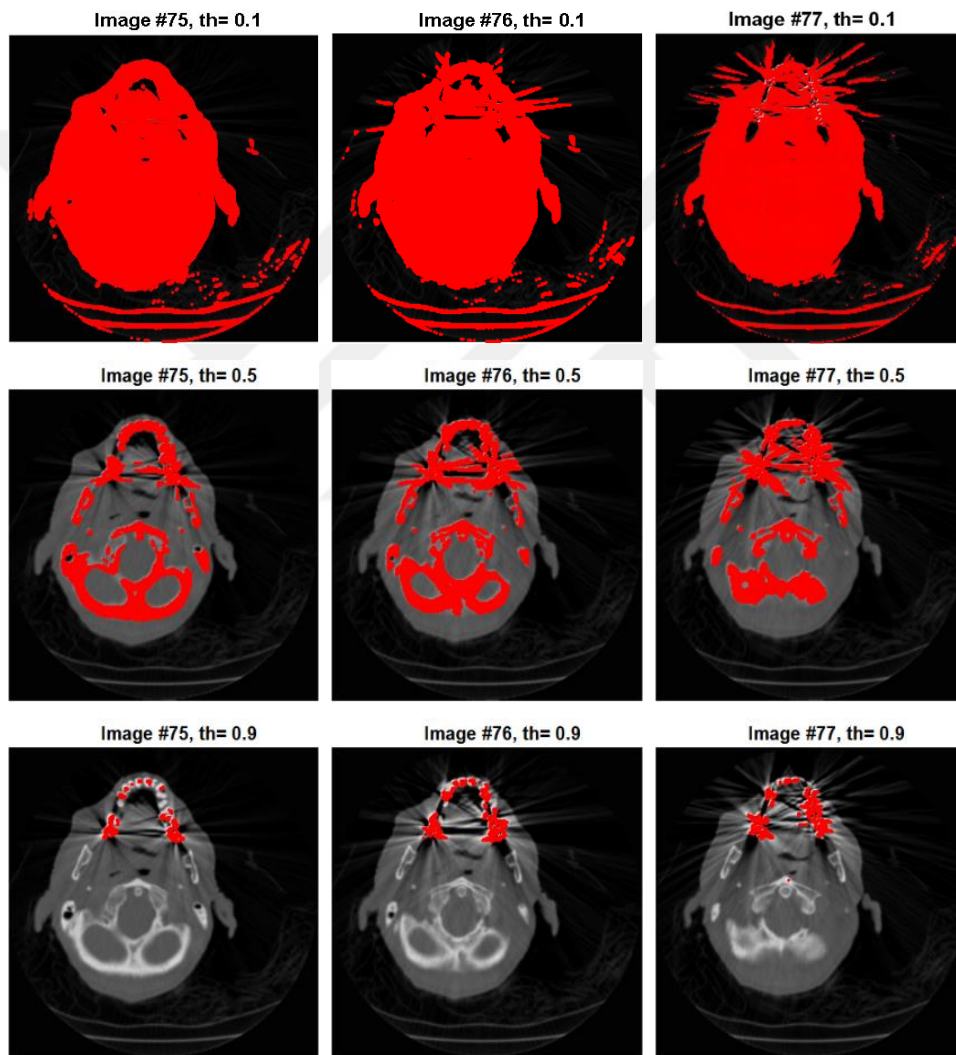


Figure 3.22. The results for different threshold values

Thresholds were tested for the most intense 2-D noisy images. In order to determine the noisy region, the threshold values of 0.1, 0.5, and 0.9 were used. In the image whose threshold values was 0.1 and 0.5, many regions were determined as red colored noisy region while a small region was determined in the case of the threshold value was 0.9.



4. DISCUSSION

In this study, 2D noisy CT cadaver images taken from different positions were used. It is aimed to correctly determine and classify the noisy pixels of CT images by using ELM classification method. In the following process, the deviations from the real pixel values of the noisy pixels are estimated and the new pixel values are calculated by considering the neighborhood relations. The study has also been compared with classification techniques of MLP-FNN and SVM and also filtering methods of Gauss, Kuwahara and NLME. Since classical statistical methods can be partially successful at the regression stage, machine learning methods of MLP-FNN and SVM which are capable of learning, having generalization ability and fewer assumptions than statistical methods, have been preferred. The proposed classification and filtering methods were implemented by using the MATLAB software package.

Denoising of noise and artifacts in the CT images used in the medical field is of great importance for the analysis of the disease. If noises and artifacts in digital images are not sufficiently reduced, the use of images on the medical field and the diagnosis of the disease will become very difficult. The process of obtaining a digital image is the process in which the noises in digital images first appear. Each step in the process brings natural phenomena to the fluctuations and adds a random number to the true brightness value of this pixel. If it was possible to know which type of noise was occurring at which step, it could be done with a zero error. However, this is not possible in practice. So denoising in the images continues to be a major problem in the field of imaging. The image is restored in order to reduce or eliminate the data losses and distortions caused by noise during the formation of an image. The apparent loss of data is noise-induced and this loss is the deviation of the noisy pixel from the true pixel value.

The purpose of this study is to correctly determine the noises in the images and calculate the new pixel values by estimating the deviations from the real pixel

values of the noisy pixels. The ELM method has been proposed to remove the disadvantages of the backpropagation based ANN method, which produces fast acting and effective results. ELM does not need to adjust hidden layer weights. Training data of the input weights are independently assigned by random methods and hidden layer weight values are calculated by analytical methods. The ELM randomly generates the input node weights and the hidden node pitch values of the neural network and calculates the output layer weights using the least squares method. In the ELM method, high generalized performance is provided for binary classification, multiple classification and regression problems by minimizing the norm of training errors and output weights. The ELM is performed with a regulated MSE and can be extended with the application of kernel methods. The Least squares method is also a standard regression method used to write the mathematical connection between two physical quantities that change in relation to each other as real as possible. In other words, this method serves to find a function curve that will go as close as possible to the data points obtained as the result of the measurement.

The MLP-FNN method, which has been used as a comparison, is now being applied to many areas and is also successful in prediction models. This method is preferred in comparison because MLP-FNN gives easy, flexible, fast, and consistent results. MLP-FNN is a system consisting of many simple process elements working in parallel with each other and determined by functions, network structure, connection weights and processes performed on the elements. A number of trial and error methods have been used in determining the MLP-FNN parameters and a large number of test procedures have been performed. In this scope; a network showing better performance on both the training set and the test set was tried by testing various combinations of parameters such as the number of hidden layers, the number of nodes in hidden layers, momentum termination, activation function, number of revolutions.

The SVM method, which was used as the second comparison method in this study, also has successful applications in predicting classification, regression and

time series in recent years. The basic idea in the SVM regression method is to find a function that reflects the true character of the current educational data in a realistic way and to find a linear discriminant function that fits the statistical learning theory. SVM can be used on classification and regression problems. Similar to the classification, kernel functions are used to process nonlinear states in the regression. SVM, which is closely related to ANN and uses a sigmoid kernel function, has a two-layer MLP-FNN. SVM models provide more convenience in the overall solution compared to the ANN models.

The filters used as comparison methods are the first step for different processes such as noise reduction, image enhancement, contribution to removal of noise from the image, and object recognition. In the filtering process, the kernel matrix determines the filter parameters and also the coefficient by which the pixel adjacent to another pixel is multiplied. The kernel matrix is defined as the conclusion of the convolution of the image. Filters are used to reveal some details in the image or to remove unwanted noises. By using image processing filters, attempts have been made to reduce the amount of image loss caused by inaccurate images as well as insufficient environmental conditions, such as illumination. For this purpose, various filtering techniques have been used to denoising in the images used in the present study.

In order to see the noises of the head of the cadaver, firstly a 3D surface model was generated by volume rendering techniques by using all the images in the database (Figure 3.3). As it is seen in the 3D surface model, the head of the cadaver appears to be covered in a material similar to the piece of cloth, the back is covered together with an object similar to pillow, and the teeth are kept together by iron-like objects. The histogram of the noisy 3D surface model was plotted and the intensity values of the pixel values of all the images in the database were found. In the histogram of the 3D model, it was seen that the intensity values of the pixels did not show a normal distribution due to noises (Figure 3.4).

The primary purpose of this study is to correctly detect the noise in the images. It is secondarily aimed to replace the noisy pixels with actual pixel values considering the neighborhood values. Firstly, noisy pixels were determined and then the pixel values around the targeted noisy pixel are located. Each noisy pixel has eight neighborhoods in its frame (f_n) and nine neighborhoods in its previous frame (f_{n-1}), and nine in the next frame (f_{n+1}) (Figure 2.13). For the sample frame, the number of features and complexity of the system increases when two previous (f_{n-2}) and two next frames (f_{n+2}) are examined. As a result of this, performance for the classification system decreased and also the success rate reduced. For each pixel value in the reference image, 26 connected pixel values were examined (eight neighborhoods in its frame, nine neighborhoods in its previous frame, and nine neighborhoods in the next frame). The new pixel values were determined by taking the average of the noiseless pixel values around the noisy pixel values. Neighborhood principles should not change any other noiseless pixel values when performing these operations. In order to detect noisy pixels, the noisiest pixels of 75th, 76th, and 77th images, which were the noisiest images, were referenced.

To generate a dataset in the classification phase, each pixel determined as noisy by the ELM system was assigned a value of 1, and a value of 0 was assigned to a pixel that were noiseless. By performing these classifications, two datasets were created. During the first stage of operations of the designed system, the dataset was created following each pixel belonging to the image being determined to either be noisy or not. To detect noisy pixels, the created dataset was trained by the ELM method and compared with other images. The dataset was divided into five equal parts by k-fold cross validation. Then, four of the parts were used as training data while one of the parts was used as test data. Therefore, the training and classification process was carried out five times through cross validation. This allowed the classification phase to be used with different data sets. As a result of this process, the overall system performance was calculated by averaging the accuracy values obtained on each fold by the ELM method. The pixel values of the sample images

used in the classification stage were extracted from the training data set and only used in the test phase. The addresses of the identified noisy pixels were visualized with a red dot. Considering the marked noisy pixel shapes in the 2D cadaver head images, it was seen that the white fringe noisy existing inside and outside of the cadaver head was correctly marked (Figure 3.2).

The optimum success rate of the system was calculated by using the ELM method with varying number of neurons in the hidden layer during training, and testing. Sigmoid, Sine, Hard Limit, Triangular Basis, and Radial Basis were considered as the activation function. The number of neurons in the hidden layer was considered between 10 and 1500. Therefore, the number of neurons in the most appropriate hidden layer was varied from 10 to 1500 with different neuron steps. When the system was trained, the training accuracy increased as the number of neurons in the hidden layer was increased, but the increase in the number of neurons did not change the success rate when the system was reached to overfitting (Figure 4.1). In the case of overfitting, the algorithm moves away from solving the underlying problem and focuses on fixing the values given to it. As a result of this situation, the algorithm could not be able to solve the problem. Increasing the number of neurons after a certain amount will reduce the performance of the system, so the number of neurons needs to be kept at an optimal level. It has been observed that the system reached overfitting at the level of 250 neurons in the hidden layer during the training phase. The success rates were obtained between 75.38 - 88.23%.

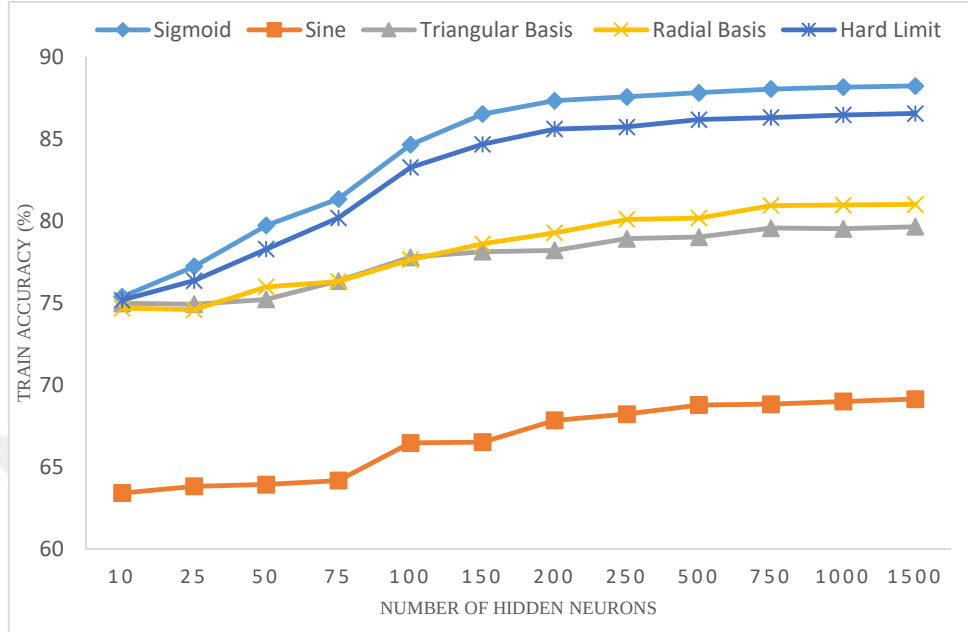


Figure 4.1. The results of the training accuracy (%) values of the ELM network classifier

In the testing phase of the ELM method, the success rate of the system was observed in the range of 75.37 - 87.20% depending on the number of neurons. The highest performance value was 87.20% for the sigmoid activation function when the number of neurons in the hidden layer was 250. When the number of neurons was exceeded 250, test success rate was observed to decrease (Figure 4.2).

The test success rate of the system decreases after a certain level. This is due to the fact that the learning algorithm is based on memorizing the system and (as a result) it is not being able to decide when it encounters a new situation. Namely, if the number of neurons exceeds the optimum level, the classification algorithm that memorizes the system due to the overfitting situation will have difficulty in deciding whether the pixels are noisy or noiseless.

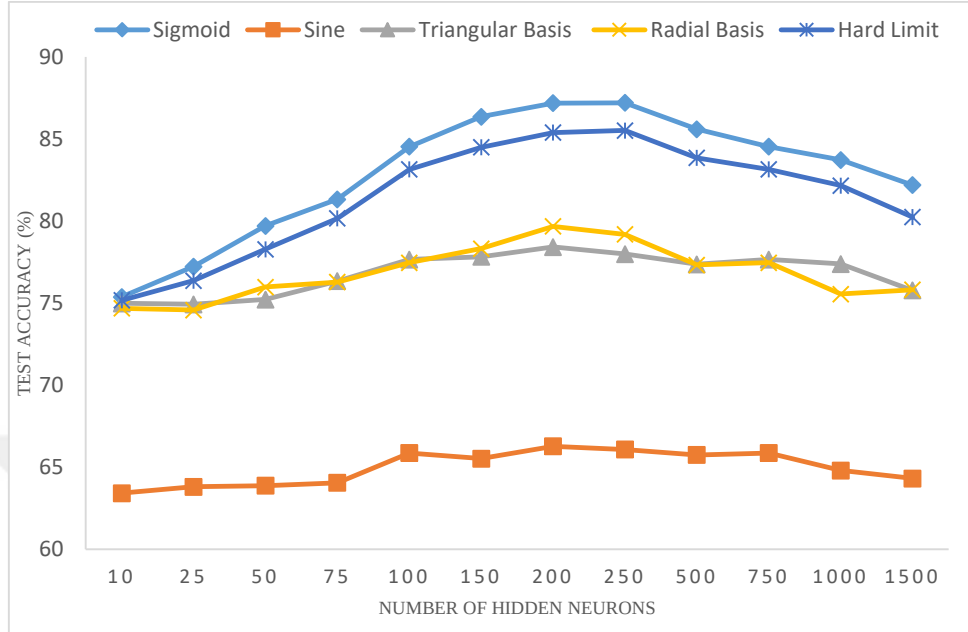


Figure 4.2. The results of the test accuracy (%) values of the ELM network classifier

After filtering the images that are exposed to noise, the performance criteria determine how similar the denoised image is to the original image. Most commonly used performance criteria are MSE, PSNR and SSIM. With these methods, the effects of different image processing algorithms on the same image were evaluated and systematically compared to determine which is more successful. The results of the classification systems are also calculated and compared to some commonly used statistical measures such as MSE, PSNR and SSIM which are obtained with the performances of the filtering methods.

In the ELM method, the success rate was increased whereas the error rate, namely MSE value, changed in an inverse proportional manner (Table 3.3). As the number of neurons increased in each layer, the MSE value decreased and an increase was observed in the values after the overfitting of the system (Figure 4.3).

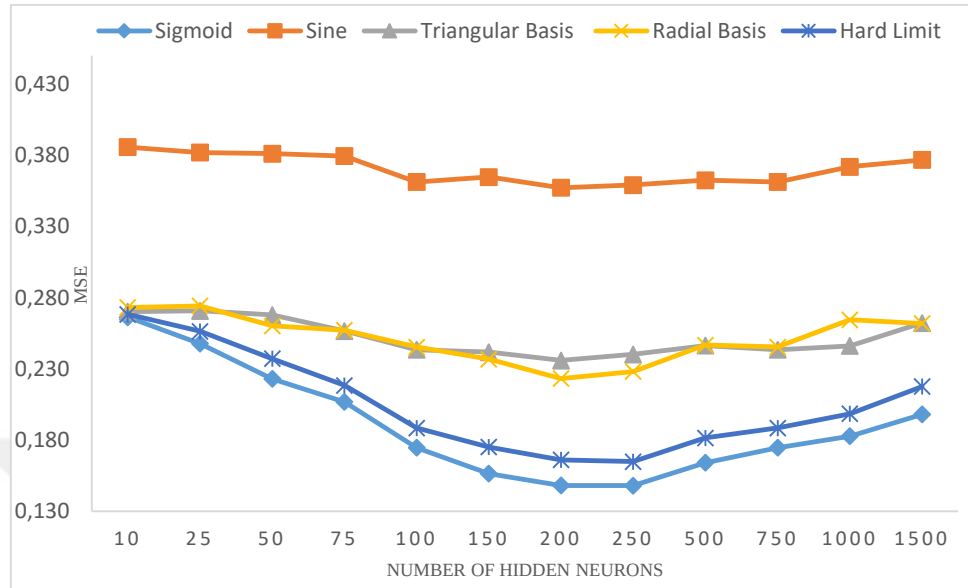


Figure 4.3. The results of the MSE values of the ELM network classifier

Increment of success rate in the ELM method was proportional to the change in the PSNR, which is the image quality metrics (Table 3.4). It was observed that the PSNR value was increased with the increase in the number of neurons in each layer, and decreased when the values were exceeded the overfitting layer of the system (Figure 4.4).

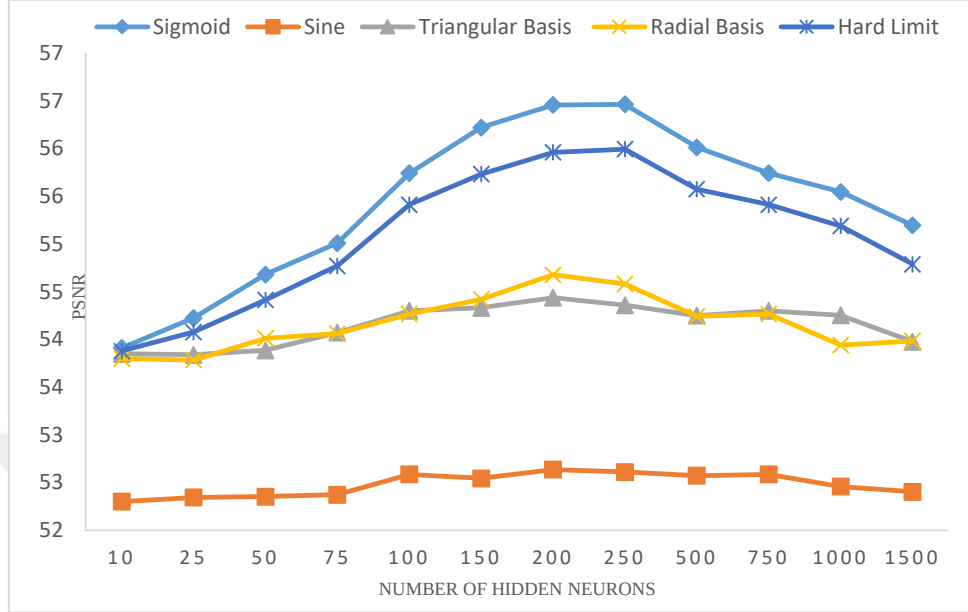


Figure 4.4. The results of the train PSNR (dB) values of the ELM network classifier

The results of the MSE, PSNR and SSIM performance criteria were compared after ELM detected the noisy and denoised the noisy pixels in the images. The results of the ELM system, MSE and PSNR performance criteria according to different neuron numbers in the hidden layer are shown in Table 4.1.

Success rates of the model for ELM, MSE and PSNR were found to be in the range of 75.37-87.20%, 0.148-0.266 and 53.911-56.46, respectively. The most successful ratios for the number of neurons 250 were ELM 87.20, MSE 0.148, and PSNR value of 56.46. A low MSE value means lesser error. When the MSE value decreases, the error rate in the image also decreases. There is an inverse relationship between MSE and PSNR values. Namely, a low value of MSE implies a high value of PSNR.

Table 4.1. The effect of changing the number of neurons in the hidden layer on the algorithm performance

Number of Neurons in the Hidden Layer	ELM (%)	MSE	PSNR (dB)
10	75.37	0.266	53.911
25	77.23	0.248	54.225
50	79.70	0.223	54.681
75	81.32	0.207	55.010
100	84.53	0.175	55.742
150	86.35	0.156	56.221
200	87.18	0.148	56.458
250	87.20	0.148	56.460
500	85.59	0.164	56.013
750	84.53	0.175	55.742
1000	83.72	0.183	55.550
1500	82.19	0.198	55.200

SSIM index values were also calculated to measure the similarity rates of the images with each other, after the noisy images of the ELM method was denoised. The SSIM values were examined between noisy images and denoised images (Table 3.6). Similarity values between images were found for a frame (f_n) referenced from noisy original images by considering the previous (f_{n-1}) and the following (f_{n+1}) frames. SSIM values were re-calculated after the images were denoised. After denoising the images, it was seen that the value of SSIM, which is in the range of 0-1, was closed to 1. The same values of the SSIM between two images mean that they are individually similar.

By considering the image neighbors of each image, the SSIM values obtained from the noisy pixel values and SSIM values of denoised pixel were compared with each other. The average SSIM value of original noisy image and denoised images in the data set reached to 0.896 and 0.946, respectively. When the results of the images given in Table 3.6 are taken into consideration, it is observed that the SSIM index value increased and approached to one (1) value.

After denoising the CT images, the 3D surface model was generated and the histogram of the model was also plotted (Figure 3.5). From the histogram of the 3D model, which was denoised, the pixel values exhibited a normal distribution (Figure 3.6). When the histogram obtained from noisy pixels and the denoised histogram were compared, it was observed that the distribution of new pixel values was successfully normalized and exhibited a normal distribution.

In addition to the ELM method for noise detection and denoising, Gausss, NLMF and Kuwahara filtering techniques were also used to test the data in the database to generate 3D surface models of the filters and then histograms were plotted. 3D surface models, histograms and success rates for each method were compared. In addition to detecting noisy pixels, the filters also detected noiseless pixel values (Figure 3.7, Figure 3.12, Figure 3.17). In medical images, real pixel values should not change during denoising pixels. Because, every pixel in the images used in the medical area has a separate significance.

Gauss filter was used to generate 3D surface models for sigma values of 0.5 (Figure 3.8) and 1.5 (Figure 3.10) and then histograms of the images were plotted. 3D surface models for filter strength values of 0.05 (Figure 3.13) and 0.2 (Figure 3.15) were performed by NLMF and also histograms of the images were plotted. 3D surface models were generated with the filter sizes of 3 (Figure 3.18) and 5 (Figure 3.20) by Kuwahara filter, and also histograms of the images were plotted. When 3D surface models of Gausss, NLMF and Kuwahara filters was examined, it was seen that was noisy and artificial objects were not denoised properly. When the histograms of the 3D models of the filters were examined, it was also observed that the pixel values did not show a normal distribution (Figure 3.9, Figure 3.11, Figure 3.14, Figure 3.16, Figure 3.19, Figure 3.21).

In this study, the performance of MLP-FNN and SVM classification methods compared to ELM was calculated for $k = 5$ value using k-fold cross validation technique by using sigmoid kernel function. 80% of the data were taken as training set and 20% was as the test set. In the testing process, a leave-one-out

cross validation method was used to test overall system accuracy. Each image of performing the dataset was included in the test set alternately. The overall system performance was calculated by taking the average of the obtained test results. In Table 4.2, the results of the ELM method are compared with classification methods of MLP-FNN, SVM and also filtering methods of Gauss, Kuwahara and NLMF. Compared methods have been tested on the noisiest samples in the database and all system performances have been calculated. According to the performance results the following successes are achieved for ELM, SVM, MLP-FNN, Gauss, Kuwahara and NLMF as 87.20%, 83.35%, 82.17%, 77.73%, 79.17% and 72.92%, respectively.

Table 4.2. Accuracy (%) values of the classification methods and filters

	Method	Image 75	Image 76	Image 77	Overall System Performance
Classification	ELM	84.45	83.78	82.74	87.20
	SVM	81.15	79.42	77.94	83.35
	MLP-FNN	80.24	78.22	76.88	82.17
Filters	Gaussian	74.79	73.14	72.49	77.73
	Kuwahara	77.51	76.59	74.97	79.17
	NLMF	67.46	66.38	65.36	72.92

Considering the literature review, some basic approaches for noise pixel estimation in the images are outlined in Table 4.3. It has been observed that the overall accuracy of the proposed system provides good results compared to other approaches in the literature.

Table 4.3 Algorithm performance comparison against image denoising of CT dataset

Reference	Dataset	Method	PSNR
Proposed Method	Stanford CT Head	ELM	56.46
(Kalavathi and Priya, 2016)	IBSR and IDEA GROUP Dataset	HLWF	45.85
(Gabralla et al., 2015)	ELCAP Public Lung Image Database	Wavelet Transform	27.12
(Chen et al., 2016)	BrainWeb: Simulated Brain	CNLM	37.18
(Yang et al., 2015)	BrainWeb: Simulated Brain	PSNLM	37.60
(Jifara et al., 2017)	Japanese Society of Radiological Technology	Deep feed forward CNN	39.25
(Yang et al., 2017a)	cadaver CT images (collected at Massachusetts General	CNN	31.12
(Kumar and Diwakar, 2016b)	ELCAP Public Lung Image Database	Haar-type wavelet transform	32.87
(Chen et al., 2017)	The Cancer Imaging Archive (TCIA)	Deep CNN	42.42
(Dabov et al., 2007)	database of natural images	BM3D	32.27
(Çelebi and Çevik, 2010)	Stanford CT dataset	Ray-leaping	52.03
	Visible woman CT dataset		51.41

The higher the PSNR value, the better the restoration of the degraded image according to the original image. The PSNR value is/was higher for evenly distributed modifications than sparsely distributed modifications. Thus, instead of modifying one pixel value by a large amount, modifying many pixels by very small amounts will result in higher PSNR. If the PSNR value is high, the MSE between the original image and reconstructed image will be very low. This implies that the image has been properly restored. Following the same logic, the restored image quality is better. According to the maximum signal value of the images, it is necessary to reduce the maximum value of the MSE between the images. In other words, the MSE value is attempted to tend towards zero. If the MSE value is calculated with two identical images, the value becomes zero and the PSNR value will be undefined.

The actual PSNR value may not be relevant, but the comparisons between the images' reconstructed values offers a measure of quality. The PSNR is an error metric utilized to compare changes in the original image and the restored image. However, the comparison of the PSNR value for different images is meaningless. For example, an image with a PSNR value of 25 dB may look better than another image with a PSNR value of 35 dB. The corresponding PSNR metric for acceptable images for use in digital radiology varies from 40 dB to 50 dB depending on the metric used (Çelebi and Çevik, 2010). In comparing an original picture and a coded picture, the PSNR figures typically range from +25 to +35 dB (Singh and Neeru, 2013). In steganography images, the best PSNR result varies from 50 to 55 dB (Jassim, 2013).

The effect of the proposed ELM method on noisy images was compared with other classification and filtering methods. According to the results obtained, it was reported that ELM produced more accurate and high success rates. As a result, comparing to the other methods, the ELM method has been successful in detecting noisy pixels and also successful results have been obtained by estimating the pixel value that will be replaced by each noisy pixel. The results show that the ELM method can be used to estimate noisy pixels and denoising.

5. CONCLUSION

The main purpose of this thesis is to facilitate more powerful diagnosis of diseases by effectively denoising the images taken from the output of medical imaging systems. In the process of obtaining medical images, due to some environmental factors such as contrast and brightness adjustments or artificial figures that exist in the images, noises may occur. If the noises of the images in the medical field are not sufficiently denoised, the use of these images as a medical purpose and diagnosis of the disease will become more challenging.

In this study, in order to determine noisy pixels and denoising the noises, a new method of resource decomposition, called ELM method, was applied. ELM is one of the artificial neural network methods. In ELM, adjusting hidden layer weights is not needed. The input weights are randomly assigned regardless of the training data but the hidden layer weight values are calculated by analytical methods. This method randomly constructs the nodal input weights and hidden nodal slope values of the neural network and the output layer weights are calculated by using the least-squares method. This method provides high generalized performance for binary classification, multiple classification and regression problems by minimizing the norm of training errors and output weights.

Noisy pixels in CT images were determined and then classified by ELM method. Neighborhood principles were used in the classification phase for each image. The coordinates of the noisy pixels were determined and the pixel values of the surroundings and the pixel values of the previous and next images were examined. Each noisy pixel value was compared with the other pixels in the dataset, and only the noiseless pixels were averaged and then it replaced with new pixel value. After denosing the CT images from the noise, a 3D surface model was performed and the histogram of the model was obtained. The histogram data was compared with the histogram after the noisy pixel was denoised. It has been observed

that the distribution of new pixel values was successfully normalized and exhibited a normal distribution.

It has been observed that, during the training phase of the ELM method, the increase in the number of neurons in the hidden layer resulted in increase in the training accuracy where it was seen that the increase in the number of neurons did not change the success rate after the system reached overfitting. Training success rates were obtained between 75.38 - 88.23 %. In the test phase, the success rate of the system was observed to be in the range of 75.37 - 87.20 % depending on the varying number of neurons. The classification system showed the highest test performance value when the number of neurons in the hidden layer was 250. It has been observed that the test success rate decreased when the number of neurons exceeded a certain level. This is due to the fact that the learning algorithm, along with the increase in the number of neurons, memorizes the system and cannot decide when it encounters a new situation. The classification algorithm that memorizes the system due to the overfitting situation will have difficulty in deciding whether the pixels are noisy or denoised. In the event of overfitting, the ELM algorithm divergence from solving the main problem and focuses on keeping the values given to it. Since increasing the number of neurons results in negative effects on the system, it is necessary to keep the number of neurons at an optimum level.

After the images are filtered by the proposed algorithm, the similarity score of the original image was performed by the performance metrics, which are quantitative methods. Performance metrics of MSE, PSNR and SSIM are more commonly known. By these methods, the effects of different image processing algorithms on the same image are evaluated and it is compared in a systematic way of determining which one is more successful. Results of classification systems were calculated by some commonly used statistical measures such as MSE, PSNR, SSIM and comparisons were performed.

According to the performance results, success rate in the ELM method, MSE, PSNR value and SSIM index are 87.20%, 0.148, 56.46 and 0.946,

respectively. In accordance with the neighborhood principle, the average SSIM value of noisy raw images is 0.896 where it is increased to 0.946 for the denoised images. For the SSIM values, it is observed that the SSIM index value has reached to a maximum value of one (1) and showed a successful increase.

For noise detection and denoising, in addition to the ELM method, the data in the database have been tested with Gauss, NLMF and Kuwahara filtering techniques, which are widely used in the literature. The 3D surface models of the filters were created and histograms were plotted. For each method, 3D surface models, histograms and success rates were compared. It was revealed that the filters cannot effectively denoise from the surface models and also the histogram results show that the pixel values do not show a normal distribution.

Moreover, the current study has also been compared with MLP-FNN and SVM classification techniques that are widely used in the literature. The MLP-FNN method, which is used as a comparison, is currently used in many prediction models. In the case of determining MLP-FNN parameters, a number of test operations have been performed. The other comparison method, SVM method, has also been recently used in successful applications of predicting classification, regression and time series.

The success rates of the comparative methods of SVM, MLP-FNN, Gauss, Kuwahara and NLMF were 83.35%, 82.17%, 77.73%, 79.17% and 72.92%, respectively. It has been observed that the classification performance values were low and some pixel values in noiseless regions have been changed by filters. Filters classify noisy pixels and noiseless pixel values. In medical images, real pixel values must not be changed in the case of denoising of noisy pixels. Each pixel in the images used in the medical field has an importance in the diagnosis and treatment process.

As a result, contrary to other common methods, the ELM method detects a local noisy pixel and it denoised noisy pixels without changing the noiseless pixel values. The effect of the ELM method on medical images has been compared and it has been shown that more accurate and higher success rates were obtained in this

method. These results show that ELM method can be used in both determining noisy pixels and in denoising images. Since data obtained from medical devices are important in diagnosing diseases, it is expected that the successful output of this study will contribute to the literature.



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CURRICULUM VITAE

He was born in Midyat / Mardin in 1985 and completed his primary and secondary school in Midyat. Between the years of 2004-2009, he was studying at the department of Computer Engineering at Kocaeli University. He finished his Master of Science (MSc) at Firat University at Computer Engineering Department. He also started Ph.D. degree in 2013 at Çukurova University at Electrical and Electronics Engineering Department. He is still a research assistant at the Department of Computer Engineering at Batman University.







APPENDIX



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