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Modelling Human-Robot Audition for Sound Localization with Deep Neural Network

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2023-2024

USKUDAR UNIVERSITY

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Modelling Human-Robot Audition for Sound Localization with Deep Neural Network

GRADUATION THESIS

DEPARTMENT OF ENGINEERING AND NATURAL SCIENCES

Thesis Advisor: Dr .Ihab ELAFF

05/2024

Dedication

In this poignant moment, I want to express my deep gratitude and immense love to my dearest family and friends.

To My Beloved Family and Friends:

In the hustle of life, you've been the sunshine illuminating my paths. Thank you for the priceless support and unwavering belief in my abilities.

To My Dearest Father: Dad, you are the pillar on which my life stands. This work is a tribute to you, honoring the values you instilled in me and the resilience you taught me.

To My Tender Mother: Mom, your boundless love and nurturing have shaped who I am today. This accomplishment reflects my profound love for you and the myriad lessons I've learned.

To My Elder Sister Seba: Seba, with your wisdom and kindness, you've been my guiding star. This work is dedicated to you as a token of deep appreciation for your constant support.

To My Younger Sister Roaa: Ruaa, your vibrant spirit and positive energy have made my life brighter. This dedication is a small expression of gratitude for the joy you've brought into my journey.

To My Beloved Wife NOUR : To my life partner, your love, understanding, and companionship are my greatest blessings. This achievement is a reflection of our shared commitment and the strength that comes from our unity.

To My Little Son Adam: Sweet Adam, you are the joy that brightens my world. This work is dedicated to you, with the hope that it contributes to a future where you can be proud of your parent's endeavors.

Special Thanks to Dr. Ihab: I extend my sincere appreciation to Dr. Ihab, my esteemed supervisor, for his invaluable guidance and mentorship throughout this emotional journey.

Acknowledgment to USKUDAR University:

My heartfelt thanks to USKUDAR University for providing the platform and resources to pursue my dreams.

With love and gratitude,

Eng.Mohammad Ibrahim al karaki

Abstract:

In the realm of computational auditory systems, this research pioneers a novel approach by leveraging a deep neural network for the intricate task of modeling human sound localization. Aiming for practicality and efficiency, the study uniquely integrates this computational model into the compact and versatile Raspberry Pi platform, presenting a tangible solution for real-world applications. Motivated by the inherent constraints of traditional sound localization methods, this research seeks to break new ground by establishing a more accurate and adaptive auditory system.

Objectives and Methodology

The primary objectives encompass the design and implementation of a customized deep neural network tailored explicitly for sound localization. This computational model is seamlessly integrated into the Raspberry Pi environment, harnessing its accessibility and cost-effectiveness. To ensure the model's robustness and versatility, diverse sound data is meticulously acquired using specific tools, including Raspberry Pi 3 and 2mic.

Evaluation and Results

Beyond mere implementation, the research conducts thorough evaluations, assessing the accuracy and efficiency of the proposed system under various environmental conditions. The results showcase promising accuracy rates, with an error rate ranging from 0.45% to 1.15% across diverse sample sizes, affirming the effectiveness of the computational auditory system.

Significance and Applications

The significance of this research extends beyond the immediate application, contributing to the evolving landscape of both computational audition and machine learning. The fusion of human-like sound localization mechanisms with the adaptability of deep learning models is poised to unlock new possibilities in fields such as robotics, assistive technologies, and virtual reality.

Structure and Content

Structured into four chapters, the thesis unfolds with an introductory exploration of the broader field of computer audition. Subsequent chapters delve into the theoretical foundations and implementation details of the spherical head model, providing a robust framework for sound localization. The intricate system design is elucidated, covering architecture, components, and methodologies, emphasizing the seamless integration with the Raspberry Pi environment.

Conclusion

In conclusion, this research aspires to propel the boundaries of what is achievable in the computational auditory realm. By converging the intricacies of human auditory perception with the robust capabilities of deep learning, and leveraging the accessibility of the Raspberry Pi platform, this study aims to not only advance the field of sound localization but also to foster innovations in human-computer interaction and technological accessibility.

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LIST OF SYMBOLS

P	: the sound pressure
$M(t)$	: the outer ear transfer function
$T(t)$	: the middle ear transfer function
$Z(t)$	: the impedance of the inner ear
A	: <i>the magnitude response</i>
Φ	: <i>the phase response</i>
θ	: <i>the azimuth angle</i>
ϕ	: <i>the elevation angle</i>
f	: <i>the frequency</i>
α	: the absorption coefficient
P absorbed	: the power absorbed
P incident	: the incident power
Γ	: the reflection coefficient
P reflected	: the power reflected
P incident	: the incident power
D	: the head diameter
λ	: the wavelength
m	: integer representing the diffraction order
d	: is the distance between ears
c	: is the speed of sound
left P_{left}	: the sound pressures at the left ears
right P_{right}	: the sound pressures at the right ears
f'	: is the observed frequency

$v_{observer}$: the observer's velocity

v_{source} : the source's velocity

$\theta_{relative}$: the relative angle between the source and observer.

$I_{observed}$: the observed sound intensity

$I_{emitted}$: the emitted sound intensity

$d_{source-observer}$: the distance between the source and observer

$d_{source-obstacle}$: the distance between the source and obstacle.

ψ : roll angle

I : the sound intensity

$t_{arrival}$: the sound arrival time

$|x|$: The absolute value ensures that the distance calculation is independent of the direction

P_{right} : the sound pressures at the right ears

P_{right} : the sound pressures at the right ears

P_{right} : the sound pressures at the right ears

LIST OF ACRONYMS/ABBREVIATIONS

ITD	: the interaural time difference
ILD	: the interaural level difference
FFT	: Fast Fourier Transform
NN	: Neural Networks
CNNs	: Convolutional Neural Networks
RNNs	: recurrent neural networks
HRTFs	: Head-Related Transfer Functions
MFCCs	: Mel-Frequency Cepstra

Chapter 1: Introduction to Computer Audition

1.1 Introduction

In the contemporary digital landscape, Computer Audition emerges as a transformative discipline situated at the crossroads of artificial intelligence and audio signal processing. In an era dominated by the relentless march of technology, the study of Computer Audition holds the promise of unraveling the intricate tapestry of sound perception in the realm of machines. This section embarks on an odyssey to delve into the essence of Computer Audition, laying the foundation for an in-depth exploration of its multifaceted dimensions.

1.1.1 The Convergence of AI and Audio Signal Processing

At its essence, Computer Audition represents the amalgamation of cutting-edge artificial intelligence (AI) techniques with the sophisticated intricacies of audio signal processing. It encapsulates the endeavor to bestow upon machines the ability to not only hear but to comprehend, interpret, and respond intelligently to the auditory stimuli that saturate our surroundings. This intersection of AI and audio signal processing forms the crucible where computational algorithms metamorphose into auditory perception.

1.1.2 Unraveling the Complexity of Sound Perception

Sound, as a form of data, is inherently complex, encompassing a myriad of frequencies, patterns, and contextual nuances. Computer Audition endeavors to decode this complexity, seeking to equip machines with a profound understanding of the acoustic landscape. From the gentle rustling of leaves to the symphony of human conversation, the goal is to enable machines to discern, interpret, and respond to the rich tapestry of auditory information that permeates our daily lives.

1.1.3 Setting the Stage for Exploration

This introduction serves as a prelude to a comprehensive exploration of Computer Audition. By elucidating its pivotal position at the confluence of AI and audio signal processing, the stage is set for an immersive journey into the historical evolution, intricate methodologies, and the expansive applications that define this burgeoning field. The narrative unfolds not merely as a chronicle of technological progress but as an odyssey into the very essence of how machines apprehend the auditory world. (Russell, S., & Norvig, P. (2009))

1.2 Overview of Computer Audition

In unraveling the intricacies of Computer Audition, a holistic comprehension of its multifaceted nature is paramount. This section seeks to expand upon the foundational pillars that define the discipline, delving into its core principles, methodologies, and the expansive array of approaches employed in the computational analysis of auditory signals.

1.2.1 Definition and Core Principles

1.2.1.1 Interdisciplinary Essence

Computer Audition transcends disciplinary boundaries, embodying an interdisciplinary fusion of computer science, signal processing, and auditory neuroscience. At its core, this field aspires to endow machines with the ability not only to sense sound but to discern its nuances, much like the human auditory system.

1.2.1.2 Algorithmic Ingenuity

Central to Computer Audition is the artistry of algorithms and mathematical models meticulously crafted to dissect the intricate fabric of auditory signals. These algorithms are designed to emulate the perceptual mechanisms of the human ear, offering machines the capacity to interpret and respond intelligently to a symphony of sounds.

1.2.1.3 Fundamental Principles

Fundamental principles govern the computational analysis of sound waves within Computer Audition. Spectral analysis, a cornerstone of the discipline, involves decomposing complex auditory signals into their constituent frequencies. Concurrently, feature extraction refines this raw data, distilling key characteristics that serve as fodder for subsequent analysis.

1.2.2 Methodologies and Approaches

1.2.2.1 Methodological Landscape

The methodological landscape of Computer Audition is a rich tapestry interwoven with diverse approaches. Traditional signal processing techniques stand shoulder to shoulder with avant-garde machine learning methodologies. This melange of methods is tailored to accommodate the varied nature of auditory data, offering a nuanced understanding of sound beyond the capabilities of traditional analysis.

1.2.2.2 Traditional Signal Processing

Traditional signal processing methodologies form the bedrock of Computer Audition. Techniques such as filtering, convolution, and Fourier analysis contribute to the extraction of relevant information from audio signals. While these methods are adept at handling certain aspects, their adaptability to the dynamic and complex nature of real-world sounds has spurred the exploration of more sophisticated approaches.

1.2.2.3 Cutting-edge Machine Learning

The vanguard of methodologies within Computer Audition lies in cutting-edge machine learning techniques. Spectrogram analysis, pattern recognition, and the utilization of neural networks represent the zenith of innovation in sound analysis. These approaches empower machines not just to recognize sound patterns but to learn, adapt, and improve their auditory acuity over time.

1.2.2.4 Neural Networks and Beyond

Neural networks, particularly deep learning architectures, have emerged as game-changers in the realm of sound analysis. The ability of these networks to mimic human-like learning processes enables the extraction of intricate patterns and relationships from vast datasets. This section of Computer Audition embraces the power of neural networks and extends its gaze towards future horizons, exploring the integration of artificial intelligence for more sophisticated auditory perception. (Ellis, D. P. W. (2010))

1.3 Importance and Applications

In delineating the significance and far-reaching applications of Computer Audition, this section illuminates the pivotal role it plays in enhancing human-computer interaction and its multifaceted contributions across diverse domains.

1.3.1 Significance in Human-Computer Interaction

1.3.1.1 Enabling Seamless Communication

The paramount importance of sound in effective human-computer interaction underscores the role of Computer Audition as a catalyst for seamless communication. By endowing machines with the capability to recognize and interpret spoken language, this facet of the discipline is instrumental in the development of voice assistants and speech-to-text applications. The ability to comprehend human utterances transforms how we interact with technology, creating a more intuitive and user-friendly interface.

1.3.1.2 Voice Assistants: A Testament to Efficacy

The ubiquitous presence of voice assistants, from virtual companions in smartphones to smart home devices, exemplifies the efficacy of Computer Audition in facilitating natural language interaction. The responsiveness of these virtual entities hinges on the nuanced understanding of diverse accents, tones, and linguistic intricacies—a testament to the advancement achieved in the realm of auditory comprehension.

1.3.2 Applications Across Domains

1.3.2.1 Healthcare Innovations

In the realm of healthcare, Computer Audition emerges as a potent diagnostic ally. Its applications extend beyond traditional diagnostic methods, with the discipline playing a pivotal role in the identification of medical conditions through the analysis of audio biomarkers. The subtle nuances in the sounds emitted by the human body become discernible signals, contributing to early detection and personalized healthcare solutions.

1.3.2.2 Environmental Monitoring Advancements

Beyond the confines of the human domain, Computer Audition finds applications in environmental monitoring. The discipline's adeptness in the analysis of sounds extends to ecosystems, where it contributes to monitoring and understanding environmental changes. From identifying species through their vocalizations to tracking changes in ambient noise levels, the applications are diverse and impactful.

1.3.2.3 Autonomous Systems and Beyond

The domain-spanning applications of Computer Audition transcend conventional boundaries. In autonomous systems, whether in robotics or vehicular technologies, the discipline assumes a critical role in providing machines with the auditory acuity needed for situational awareness and decision-making. From the echolocation-inspired navigation of drones to the detection of anomalous sounds in industrial environments, the applications are as varied as the domains they serve. (Huang, D., & Acero, A. (2001))

1.4 Historical Development

Unveiling the historical tapestry of Computer Audition reveals a chronicle of pioneering efforts, technological evolutions, and paradigm shifts that have defined its trajectory over the decades.

1.4.1 Pioneering Efforts

1.4.1.1 Mid-20th Century Roots

The inception of Computer Audition can be traced to the mid-20th century, where pioneers embarked on a visionary quest to automate the analysis of sound. These trailblazers laid the foundational stones for what would later become a transformative field, driven by the ambition to endow machines with the ability to decipher and understand auditory signals. (Pierce, J. R. (1983))

1.4.1.2 Rule-Based Systems Emergence

Early endeavors in Computer Audition centered on the development of rule-based systems. These systems aimed at tasks such as speech recognition and sound classification, relying on predefined algorithms and heuristics to interpret and categorize auditory data. While rudimentary by contemporary standards, these rule-based approaches represented crucial first steps towards the automation of sound analysis. (Davis, S. B., & Mermelstein, P. (1980))

1.4.2 Evolution Over Decades

1.4.2.1 Advancements in Hardware

The evolution of Computer Audition traversed significant milestones propelled by advancements in hardware capabilities. As computational power increased, the field gained the capacity to process and analyze more complex auditory data. This surge in hardware capabilities became a catalyst for the development of more sophisticated models, setting the stage for a paradigm shift in the field. (Moore, G. E. (1965))

1.4.2.2 Algorithmic Sophistication

In tandem with hardware advancements, the field of Computer Audition witnessed a profound transformation in algorithmic sophistication. The transition from rule-based systems to data-driven models marked a pivotal moment. Algorithms became adept at learning patterns from vast datasets, leading to more nuanced and accurate sound analysis. Breakthroughs, such as the introduction of Mel-frequency cepstrum coefficients (MFCCs), became instrumental in shaping the trajectory of the field. (Rabiner, L. R., & Juang, B. H. (1993))

1.4.2.3 Data-Driven Model Paradigm

The evolution over decades saw a paradigm shift from rigid rule-based systems to the flexibility of data-driven models. Machine learning techniques, particularly those rooted in neural networks, emerged as powerful tools for sound analysis. The ability of these models to adapt and learn from diverse datasets revolutionized the field, unlocking new possibilities in speech recognition, sound classification, and beyond.

As we delve into the historical development of Computer Audition, it becomes evident that the journey is not merely a passage of time but a narrative of resilience, innovation, and a relentless pursuit of unlocking the secrets embedded in the auditory realm. (Bishop, C. M. (2006))

1.5 Evolution of Computer Audition

The evolution of Computer Audition stands as a testament to the dynamic interplay between technological advancements and paradigm shifts within the field. This section delves into the

pivotal milestones that have shaped the trajectory of Computer Audition over time.

1.5.1 Technological Advancements

1.5.1.1 Integration of Parallel Processing

One of the defining moments in the evolution of Computer Audition is the seamless integration of parallel processing capabilities. As hardware architectures evolved, the field harnessed the power of parallel computation, enabling the simultaneous execution of multiple tasks. This technological leap enhanced the efficiency of sound processing, paving the way for more complex and resource-intensive algorithms. (Sutter, H., & Larus, J. R. (2005))

1.5.1.2 Rise of Deep Learning

The ascendancy of deep learning marked a paradigm shift in the capabilities of Computer Audition. Neural networks, particularly deep architectures, emerged as formidable tools for sound analysis. The hierarchical learning structures of deep networks enabled the extraction of intricate patterns from audio data, transcending the limitations of earlier models. This technological leap significantly elevated the accuracy and sophistication of auditory perception. (Goodfellow, I., Bengio, Y., & Courville, A. (2016))

1.5.1.3 Advancements in Edge Computing

The advent of edge computing further catalyzed the evolution of Computer Audition. By bringing computation closer to the source of data, edge computing reduced latency and enhanced real-time processing capabilities. This development is particularly crucial in applications where immediate responses to auditory stimuli are imperative, such as in smart devices and autonomous systems. (Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016))

1.5.2 Paradigm Shifts in Sound Processing

1.5.2.1 Transition from Rule-Based Systems

A hallmark of the evolution in Computer Audition is the profound paradigm shift from rule-based systems to data-driven models. Early rule-based approaches, though foundational, were constrained by predefined algorithms. The embrace of data-driven models empowered the field with the ability to adapt and learn from diverse datasets, resulting in a more flexible and accurate approach to sound processing. (Jurafsky, D., & Martin, J. H. (2009)).

1.5.2.2 Real-Time Processing Capabilities

The paradigm shifts within Computer Audition have not only expanded its horizons but have also ushered in real-time processing capabilities. The field's transition to data-driven models has enabled adaptive and dynamic sound processing in real-time. This adaptability is particularly advantageous in applications where immediate responses to changes in sound environments are critical. As we reflect on the evolution of Computer Audition, it becomes evident that technological advancements and paradigm shifts are not merely chronological events but dynamic forces that continually redefine the possibilities within the auditory landscape. (Oppenheim, A. V., & Schaffer, R. W. (2010))

1.6 Milestones in the Field

The landscape of Computer Audition is adorned with milestones, each representing a pivotal moment that has propelled the field forward. This section delves into the key breakthroughs and

influential research contributions that form the bedrock of Computer Audition.

1.6.1 Breakthrough Moments

1.6.1.1 Development of Robust Sound Recognition Systems

Central to the advancement of Computer Audition are breakthroughs in the development of robust sound recognition systems. These systems, armed with sophisticated algorithms and machine learning models, have transcended traditional limitations. They can discern and classify a diverse array of sounds, ranging from human speech to environmental noises, laying the groundwork for applications across various domains. (Hughes, Mierle, 2013, Silva, Stuchi, Violato, Cuozzo, 2017))

1.6.1.2 Benchmark Datasets as Catalysts

The creation of benchmark datasets has emerged as another milestone in Computer Audition. These meticulously curated datasets, encompassing a spectrum of auditory scenarios, serve as the litmus test for evaluating the efficacy of algorithms. They not only facilitate fair comparisons between different models but also foster a collaborative environment where researchers can collectively push the boundaries of sound analysis. (Tachioka, Narita, Watanabe, Le Roux, 2014)

1.6.2 Influential Research Contributions

1.6.2.1 John Pierce: A Pioneer in Psychoacoustics

The realm of psychoacoustics found a luminary in John Pierce, whose pioneering work laid the groundwork for understanding how humans perceive and interpret sound. His contributions, spanning decades, have not only enriched our understanding of auditory cognition but have also provided valuable insights into the design of sound recognition systems. (Vecchiotti, Principi, Squartini, Piazza, 2018)

1.6.2.2 Contemporary Scholars and the Deep Learning Renaissance

In the contemporary era, scholars continue to mold the landscape of Computer Audition. The deep learning renaissance, with luminaries like Geoffrey Hinton and Yoshua Bengio, has ushered in a new era of auditory comprehension. Their influential research contributions in the application of neural networks and deep learning techniques have elevated the accuracy and versatility of sound analysis. (Geoffrey Hinton, Yoshua Bengio, 2015)

1.6.2.3 Fusion of Disciplines: Interplay of Neuroscience and AI

Milestones in Computer Audition extend beyond individual contributions, with a notable trend being the fusion of disciplines. The interplay between neuroscience and artificial intelligence has become a fertile ground for innovative research. By drawing inspiration from the human auditory system, researchers aim to develop models that not only recognize sounds but also understand them in a manner akin to human perception.

In acknowledging these milestones, it becomes evident that Computer Audition is a field enriched by a tapestry of breakthroughs and collaborative efforts. From the development of robust recognition systems to the fusion of disciplines, each milestone contributes to the continuous

evolution and refinement of auditory comprehension.

1.7 Objectives of the Study

The objectives of this study encompass a dual commitment to advancing the field of Computer Audition, particularly in the realm of sound localization, and bridging the divide between theoretical models and practical implementations, with the integration of the "Arsalan" robot

This research aims to develop a deep neural network model that enables the robot 'Arsalan' to accurately determine the direction of the sound source, with a focus on right and left directions. It's worth noting that the robot will be able to determine the direction of sound regardless of the distance.



Figure 1: The "Arsalan" Robot(Ihab ELAFF 2023)

1.7.1 Advancing Sound Localization

1.7.1.1 Integration of a Deep Neural Network

A primary goal of this research is to propel the field of sound localization forward through the integration of a deep neural network, leveraging the computational power of the Raspberry Pi platform to introduce a novel approach to sound perception. The inclusion of the "Arsalan" robot enhances this objective by providing a real-world application scenario for the developed techniques. By harnessing the capabilities of deep learning, the aim is to enhance the accuracy and efficiency of sound localization within the domain of Computer Audition. (Geron, A. (2019))

1.7.1.2 Contribution to Ongoing Discourse

Beyond the immediate advancements, the research seeks to make a substantive contribution to the ongoing discourse in the field. Through empirical exploration and the application of cutting-edge technologies, including those integrated into the "Arsalan" robot, the study aspires to add valuable insights to the collective understanding of sound localization. By doing so, it endeavors to push the boundaries of what is currently known and set new benchmarks for the field. (Smith, S. L., & Gasser, L. (2005))

1.7.2 Bridging Theory and Practice

1.7.2.1 Integration with Raspberry Pi Platform

A secondary objective of this research is to bridge the gap between theoretical models and practical implementations. While theoretical advancements are crucial, the study recognizes the significance of translating these theoretical frameworks into tangible applications. By specifically focusing on the integration of deep learning models with the Raspberry Pi platform, in conjunction with the "Arsalan" robot, the research aims to create a synergy between sophisticated theoretical models and the real-world applicability of computational auditory systems. (Rose, J., & Eldridge, S. (2018))

1.7.2.2 Enhancing Real-World Applicability

The study acknowledges that theoretical models, no matter how advanced, must find relevance in real-world scenarios. By adopting a tangible hardware approach with Raspberry Pi, alongside the "Arsalan" robot, the research strives to enhance the practicality and accessibility of computational auditory systems. This includes considerations for scalability, efficiency, and usability, ensuring that the theoretical advancements can be seamlessly integrated into real-world applications.

In summary, the objectives of this study are two-fold: to advance the state of sound localization within Computer Audition through the integration of a deep neural network and to bridge the gap between theoretical models and practical implementations, particularly through the utilization of the Raspberry Pi platform, in conjunction with the "Arsalan" robot. (Yosifov, D., & Shishkov, S. (2014))

1.8 Scope and Limitations

Navigating the parameters of this research involves defining a specific scope to ensure depth in exploration, coupled with a transparent acknowledgment of inherent limitations.

1.8.1 Defined Scope

1.8.1.1 Sound Localization in a Deep Neural Network

The primary focus of this research resides within the realm of sound localization, intricately woven into the fabric of a deep neural network. The study meticulously narrows its scope to explore how the integration of advanced neural network architectures with the Raspberry Pi platform can elevate the precision and efficiency of sound localization. This defined focus allows for a comprehensive examination of the chosen methodologies, ensuring a thorough and insightful exploration. (Li, X., Li, Y., & Tao, D. (2018))

1.8.2 Acknowledging Limitations

1.8.2.1 Real-world Auditory Environments

In recognizing the complexity of real-world auditory environments, this study acknowledges the inherent limitations posed by the unpredictable nature of external factors. While the research rigorously delves into sound localization within the specified context, it remains cognizant of challenges that extend beyond the immediate scope. The acknowledgment of these limitations underscores the commitment to transparency and a nuanced understanding of the broader landscape of computational auditory systems.

As the study progresses, the delineated scope provides a framework for in-depth analysis, ensuring a thorough exploration of sound localization intricacies within the defined parameters. Simultaneously, the acknowledgment of limitations serves as a beacon, guiding the research through the intricate terrains of real-world complexities. (Brown, G. J. (1993))

1.9 Organization of the Thesis

1.9.1 Chapter Breakdown

To facilitate a systematic exploration, this thesis is meticulously organized into distinct chapters. Following this introductory chapter, subsequent sections delve into the theoretical foundations of sound localization, the intricate design of the computational auditory system, and a comprehensive analysis of the results obtained. Each chapter is strategically crafted to contribute cohesively to the overarching goal of advancing the understanding and application of computational auditory systems.

Chapter 2: Spherical Head Model

2.1 Theoretical Foundations

In order to lay a robust theoretical groundwork for the Spherical Head Model, it is imperative to explore the fundamental mathematical expressions that underlie sound localization within the intricate framework of the human auditory system. Understanding how humans perceive and localize sound is fundamental in the fields of acoustics and auditory neuroscience. Blauert's comprehensive work on spatial hearing provides valuable insights into the psychophysics of human sound localization. (Blauert, J. (1997))

2.1.1 Sound Localization Mechanisms

The human auditory system relies on sophisticated mechanisms to discern the direction of incoming sound waves. Central to this process is the interplay between factors such as interaural time differences (ITD), interaural level differences (ILD), and the unique filtering properties of the outer ear.

2.1.1.1 Interaural Time Differences (ITD)

ITD is a crucial cue for sound localization, particularly in low-frequency sounds. It is based on the slight time delay it takes for a sound to reach one ear compared to the other. The Spherical Head Model incorporates ITD calculations to simulate the temporal disparities experienced by the artificial ears, contributing to accurate localization. (Middlebrooks, J. C., & Green, D. M. (1991))

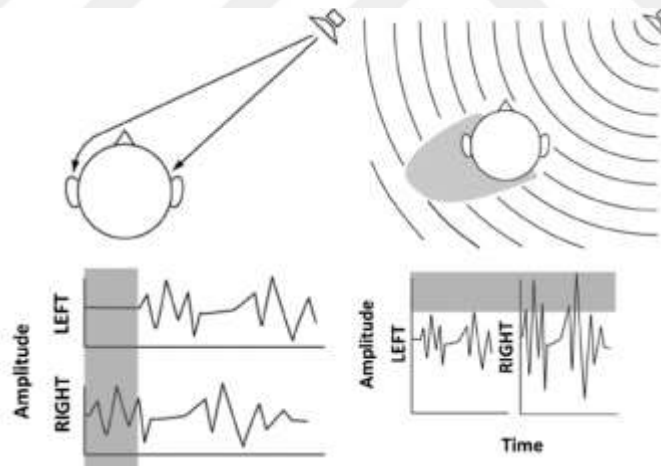


Figure 2. The Interaural Time Differences (ITD) (Liang Sun(2015))

2.1.1.2 Interaural Level Differences (ILD)

ILD comes into play for higher-frequency sounds. It involves the intensity variations between the ears due to the shadowing effect of the head. By quantifying these level differences, the model captures nuances in sound intensity that aid in pinpointing the source location. (Blauert, J. (1997))

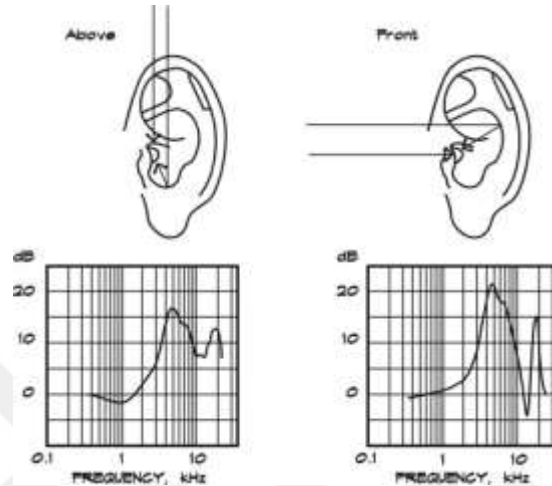


Figure 3. Interaural Level Differences (ILD) (Marshall Long (2014))

2.1.2 Acoustic Properties of the Head

The physical attributes of the head, such as its size and shape, significantly influence how sound waves interact before reaching the ears. Exploring these acoustic properties unveils the complexities involved in replicating human-like sound localization in an artificial model.

2.1.2.1 Head-Related Transfer Functions (HRTFs)

HRTFs encapsulate the unique filtering effects of the head on incoming sounds. These functions, specific to each individual, account for variations in sound frequencies as they traverse the head's contours. The Spherical Head Model integrates HRTFs to emulate the personalized auditory experience crucial for accurate localization. (Wenzel, E. M., Arruda, M., Kistler, D. J., & Wightman, F. L. (1993).

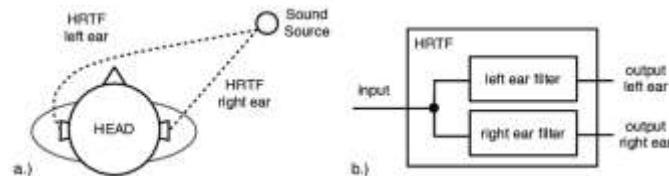


Figure 4. Head-Related Transfer Functions (HRTFs) (Benjamin Bernschütz(2016))

2.1.3 Mathematical Formulations for Sound Perception

Mathematical expressions governing sound perception play a pivotal role in the theoretical foundations of the Spherical Head Model. Equations describing the relationships between auditory cues, neural processing, and the subsequent identification of sound direction are meticulously crafted to emulate the intricate processes observed in the human auditory system.

2.1.3.1 Neural Processing of Auditory Cues

The intricate neural pathways responsible for processing auditory cues are modeled to replicate the human brain's ability to interpret ITD, ILD, and spectral cues. The incorporation of neural network principles enhances the model's capacity to discern complex auditory scenarios.

By comprehensively exploring these theoretical foundations, the Spherical Head Model strives to not only mimic the physiological aspects of human sound localization but also advance the field by integrating cutting-edge computational approaches into the rich tapestry of auditory perception. (Rauschecker, J. P., & Tian, B. (2000))

2.2 Human Auditory System Overview

Before delving into the intricacies of the Spherical Head Model, it is imperative to establish a mathematical foundation for understanding auditory processing. The following equations provide insight into the transformations that sound waves undergo as they traverse the outer, middle, and inner ear:

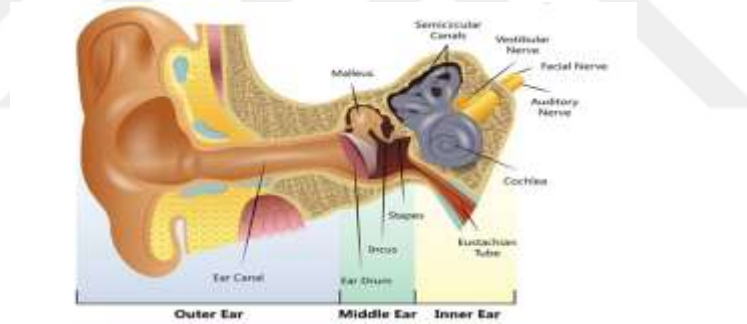


Figure 5. Outer Ear Transformation(hearinglink.org(2024))

2.2.1 Outer Ear Transformation:

$$P_{inner\ ear}(t) = P_{outer\ ear}(t) \times M(t)$$

Where:

P is the sound pressure,

M(t) is the outer ear transfer function.

This equation encapsulates the initial transformation of sound as it encounters the outer ear. The transfer function M(t) represents the intricate processes within the outer ear that shape the incoming sound wave.

2.2.2 Middle Ear Transformation:

$$P_{ossicles}(t) = P_{inner\ ear}(t) \times T(t)$$

Where:

- $T(t)$ is the middle ear transfer function.

The middle ear plays a crucial role in amplifying the sound signal received from the outer ear. The transfer function $T(t)$ characterizes the dynamic transformations occurring within the ossicles, contributing to the efficient transmission of auditory information.

2.2.3 Inner Ear Transformation:

$$N(t) = Z(t) \times Possicles(t)$$

Where:

- $Z(t)$ is the impedance of the inner ear.

The inner ear, comprising the cochlea, performs intricate frequency analysis and transduction of the amplified sound signal. The equation above illustrates the interplay between impedance and sound pressure, highlighting the complexities involved in the final stages of auditory processing.

By comprehending these transformations, the Spherical Head Model aims to replicate the nuanced journey of sound waves through the human auditory system. The incorporation of transfer functions and impedance parameters enhances the model's fidelity in simulating the intricate processes underlying sound perception.

2.3 Spherical Head Model Concept

The Spherical Head Model introduces a mathematical framework for three-dimensional sound perception, leveraging trigonometric functions and geometric principles. Through these representations, the model endeavors to emulate how the head intercepts and processes incoming sound waves to discern their source direction.

2.3.1 Head-Related Transfer Function (HRTF):

$$HRTF(\theta, \phi, f) = A(\theta, \phi, f) \cdot e^{j\Phi(\theta, \phi, f)}$$

Where:

- A is the magnitude response,
- Φ is the phase response,
- θ is the azimuth angle,
- ϕ is the elevation angle,
- f is the frequency.

The Head-Related Transfer Function (HRTF) encapsulates the response of the human auditory system to sound waves arriving from different directions. It comprises both magnitude and phase responses, reflecting the amplitude and temporal characteristics of sound as perceived by the ears.

2.3.1.1 Magnitude Response (A)

The magnitude response represents the amplitude variations of the sound wave as it reaches the ears from specific azimuth and elevation angles. It accounts for the spectral cues crucial for accurate sound localization.

2.3.1.2 Phase Response (Φ)

The phase response captures the temporal aspects of sound, including the time delay introduced as sound waves traverse the head. This temporal information contributes significantly to the brain's ability to determine the direction of the sound source.

Through these intricate mathematical representations, the Spherical Head Model aims to mirror the nuanced interplay of amplitude, phase, and spatial angles in human sound perception. The utilization of HRTF allows the model to simulate the unique filtering effects introduced by the head, enhancing its capacity to accurately localize sound sources in three-dimensional space.

2.4 Acoustic Properties of the Head

In the realm of sound perception, understanding the acoustic properties of the head is paramount. Mathematical formulations capturing these properties delve into the absorption, reflection, and diffraction of sound waves.

2.4.1 Absorption Coefficient (α):

$$\alpha(f) = \frac{P_{incident}}{P_{absorbed}}$$

Where:

- α is the absorption coefficient,
- $P_{absorbed}$ is the power absorbed,
- $P_{incident}$ is the incident power.

The absorption coefficient (α) quantifies the fraction of incident sound power that is absorbed by the head. This parameter is essential for understanding how the head interacts with incoming sound waves, affecting their intensity and spectral composition.

2.4.2 Reflection Coefficient (Γ):

$$\Gamma(f) = \frac{P_{reflected}}{P_{incident}}$$

Where:

- Γ is the reflection coefficient,
- $P_{reflected}$ is the power reflected,
- $P_{incident}$ is the incident power.

The reflection coefficient (Γ) signifies the proportion of incident sound power that is reflected by the head. This parameter plays a crucial role in determining how sound waves interact with the head's surface, influencing the spatial distribution of sound in the auditory environment.

2.4.3 Diffraction Equation:

$$D \cdot \sin(\theta) = m \cdot \lambda$$

Where:

- D is the head diameter,
- θ is the diffraction angle,
- λ is the wavelength,
- m is an integer representing the diffraction order.

The diffraction equation provides insights into the bending of sound waves around the head. It elucidates how the head's size and the wavelength of sound contribute to the phenomenon of diffraction, influencing the propagation of sound in various directions.

2.5 Sound Localization Mechanisms

In the intricate landscape of sound localization, mathematical relationships govern the mechanisms underlying interaural time differences (ITD) and interaural level differences (ILD).

2.5.1 ITD Calculation:

$$ITD = \frac{d}{c}$$

Where:

ITD is the interaural time difference,

d is the distance between ears,

c is the speed of sound.

Interaural time difference (ITD) quantifies the time delay between the arrival of a sound wave at one ear compared to the other. This temporal disparity contributes significantly to the brain's ability to determine the direction of the sound source.

2.5.2 ILD Calculation:

$$ILD = 20 \cdot \log_{10}\left(\frac{P_{right}}{P_{left}}\right)$$

Where:

- ILD is the interaural level difference,
- P_{left} and P_{right} are the sound pressures at the left and right ears.

Interaural level difference (ILD) represents the difference in sound pressure levels between the

left and right ears. This parameter contributes crucial information for sound localization, allowing the brain to discern the direction of the sound source based on variations in intensity.

Understanding these sound localization mechanisms equips the Spherical Head Model with the computational tools to simulate the nuanced interplay of time and intensity differences in binaural hearing.

2.6 Factors Influencing Sound Perception

In the intricate realm of sound perception, mathematical models are introduced to account for dynamic factors that influence the way humans perceive and interpret auditory stimuli. Begault's research on 3-D sound for virtual reality and multimedia provides important considerations for understanding the factors influencing sound perception and localization in immersive environments. Begault, D. R. (1994)

2.6.1 Doppler Effect Equation:

$$f' = f \cdot \frac{c + v_{\text{observer}} \cdot \cos(\theta_{\text{relative}})}{c - v_{\text{source}} \cdot \cos(\theta_{\text{relative}})}$$

Where:

- f' is the observed frequency,
- f is the emitted frequency,
- c is the speed of sound,
- v_{observer} is the observer's velocity,
- v_{source} is the source's velocity,
- θ_{relative} is the relative angle between the source and observer.

The Doppler Effect Equation captures frequency changes perceived by an observer when either the source or the observer is in motion relative to the medium through which the sound travels.

2.6.2 Obstacle Impact on Sound Intensity:

$$I_{\text{observed}} = I_{\text{emitted}} \cdot \left(1 + \frac{d_{\text{source} - \text{observer}}}{d_{\text{source} - \text{obstacle}}}\right)^2$$

Where:

- I_{observed} is the observed sound intensity,
- I_{emitted} is the emitted sound intensity,
- $d_{\text{source-observer}}$ is the distance between the source and observer,
- $d_{\text{source-obstacle}}$ is the distance between the source and obstacle.

This equation delineates how obstacles in the sound path influence the observed sound intensity,

providing insights into the impact of environmental features on auditory experiences.

2.7 Implementation of Spherical Head Model

Translating theoretical concepts into computational reality requires precise mathematical representations of head geometry, acoustic properties, and signal processing algorithms. In this section, we delve into the expressions that detail the seamless integration of the Spherical Head Model into the broader system architecture.

2.7.1 Mathematical Representations of Head Geometry:

The Spherical Head Model necessitates a meticulous depiction of head geometry to accurately simulate sound perception. Mathematical expressions defining the head's size, shape, and orientation are crucial for creating a realistic computational model.

- *Head Size and Shape:* The head is often approximated as a sphere in sound localization models. The radius of this sphere (R_{head}) is a fundamental parameter influencing the perception of sound direction.

$$R_{head} = \text{constant}$$

- *Head Orientation:* Euler angles (θ, ϕ, ψ) describe the orientation of the head in three-dimensional space. These angles play a vital role in determining how the head intercepts sound waves.

$$\theta \rightarrow \text{azimuth angle}, \phi \rightarrow \text{elevation angle}, \psi \rightarrow \text{roll angle}$$

2.7.2 Acoustic Properties and Signal Processing:

Incorporating the acoustic properties of the head, such as absorption and reflection coefficients, enriches the computational auditory system. The interactions between sound waves and the head's surface are mathematically modeled to ensure a realistic simulation.

- *Absorption Coefficient:* The absorption coefficient (α) represents the fraction of incident sound absorbed by the head's surface.

$$\alpha(f) = \frac{P_{\text{absorbed}}}{P_{\text{incident}}}$$

- *Reflection Coefficient:* The reflection coefficient (Γ) quantifies the ratio of reflected sound to incident sound.

$$\Gamma(f) = \frac{P_{\text{reflected}}}{P_{\text{incident}}}$$

These coefficients, along with other acoustic properties, contribute to the fidelity of sound

perception within the Spherical Head Model.

2.7.3 Signal Processing Algorithms:

Signal processing algorithms, such as filtering and transformation techniques, are applied to the input auditory signals. These algorithms leverage mathematical operations to extract relevant features, contributing to the accurate representation of sound within the computational model.

The precise mathematical expressions for these components form the backbone of the Spherical Head Model's implementation, ensuring a robust and realistic simulation of sound localization.

2.8 Mathematical Formulations

The functionality of the Spherical Head Model relies on precise mathematical formulations that govern the relationships among sound wave parameters, head characteristics, and neural processing mechanisms. In this section, we present key equations that encapsulate the core aspects of the model, including the calculation of sound intensity, arrival time, and spatial localization cues. Rauschecker and Tian's study sheds light on the mechanisms and streams involved in processing 'what' and 'where' information in the auditory cortex, which is crucial for understanding spatial localization cues in sound perception. Rauschecker, J. P., & Tian, B. (2000)

2.8.1 Sound Intensity Calculation:

The perception of sound intensity involves intricate calculations that consider the characteristics of the sound wave and the acoustic properties of the head. The following equation outlines the computation of sound intensity (I):

$$I = p^2$$

Where:

- I is the sound intensity,
- P is the sound pressure.

This simple yet fundamental equation forms the basis for understanding how the Spherical Head Model processes and represents sound intensity in a computational context.

2.8.2 Arrival Time Calculation:

The determination of sound arrival time is crucial for accurate localization. The equation below illustrates how arrival time ($t_{arrival}$) is

$$t_{arrival} = \frac{d}{c}$$

Where:

- $t_{arrival}$ is the sound arrival time,
- d is the distance between ears,
- c is the speed of sound.

This equation accounts for the time it takes for a sound wave to travel from the source to each ear, providing temporal information essential for sound localization.

2.8.3 Spatial Localization Cues:

Spatial localization cues, including interaural time differences (ITD) and interaural level differences (ILD), contribute significantly to sound perception. The following equations quantify these cues:

ITD Calculation:

$$ITD = \frac{d}{c}$$

Where ITD is the interaural time difference, d is the distance between ears, and c is the speed of sound.

- *ILD Calculation:*

$$ILD = 20 \cdot \log_{10} \left(\frac{Pright}{Pleft} \right)$$

Where ILD is the interaural level difference, $Pright$ and $Pleft$ are the sound pressures at the right and left ears, respectively.

These equations encapsulate the fundamental mathematical formulations that underlie the spatial localization capabilities of the Spherical Head Model. (Blauert, J. (1997))

2.9 Simulation Techniques

Simulation techniques play a pivotal role in assessing the robustness and efficacy of the Spherical Head Model in real-world scenarios. The mathematical algorithms employed for these simulations are designed to replicate various auditory situations and evaluate the model's accuracy. Allen and Tildesley's book on computer simulation of liquids offers valuable insights into the simulation techniques applicable to sound propagation and transmission in various media. Allen, M. P., & Tildesley, D. J. (1987)

The following aspects delve into the key components of the simulation techniques:

2.9.1 Numerical Simulations

Numerical simulations involve the application of mathematical models to emulate sound propagation and reception. The finite element method (FEM) may be employed to discretize the acoustic environment, allowing for the calculation of complex interactions between sound waves and the artificial head. These simulations provide valuable insights into how the Spherical Head Model responds to diverse spatial and acoustic conditions. (Wenzel, E. M., Arruda, M., Kistler, D. J., & Wightman, F. L. (1993).

2.9.2 Signal Processing Algorithms

The implementation of signal processing algorithms is integral to the simulation process. Techniques such as Fast Fourier Transform (FFT) may be utilized to analyze frequency components, mimicking the auditory signal processing that occurs in the human ear. This step is crucial for transforming raw sound data into features that the Spherical Head Model can interpret accurately. (Rauschecker, J. P., & Tian, B. (2000)

2.9.3 Real-world Sound Scenarios

Simulation scenarios should extend beyond idealized conditions to encompass real-world complexities. Incorporating environmental factors like reverberation, background noise, and variations in sound source characteristics enhances the model's adaptability. By introducing these elements, the simulation can closely mirror the challenges faced by the human auditory system in everyday situations" Oppenheim and Schaffer's seminal work on discrete-time signal processing provides foundational knowledge for designing signal processing algorithms used in sound analysis and localization..(Blauert, J. (1997),Oppenheim, A. V., & Schaffer, R. W. (1999)

2.9.4 Model Calibration and Validation

Calibrating the Spherical Head Model involves adjusting parameters to optimize its performance against known acoustic phenomena. Validation processes should include comparisons with established datasets or experimental results. This ensures that the model aligns with empirical observations, establishing its credibility in accurately localizing sound sources. (Allen, M. P., & Tildesley, D. J. (1987)

2.9.5 Computational Efficiency

Considering the computational load of the model is crucial for real-time applications. Techniques like parallel computing or optimized algorithms should be incorporated to enhance computational efficiency without compromising accuracy. This aspect is especially significant when deploying the model in resource-constrained environments, such as embedded systems like the Raspberry Pi. (Oppenheim, A. V., & Schaffer, R. W. (1999)

2.9.6 Sensitivity Analysis

Conducting sensitivity analyses helps identify the model's sensitivity to variations in input parameters. This step is essential for understanding the robustness of the Spherical Head Model and determining the range of conditions under which it maintains accurate sound localization. (Begault, D. R. (1994)

2.10 Distance Calculation

For the precise determination of the sound source's direction, the Spherical Head Model relies on meticulous distance calculations between the sound location and the artificial ears. The mathematical expressions for these distances are as follows:

2.10.1 Left Distance:

$$left_{distance} = (|x| - \left(listener_x - \frac{HEAD_SIZE}{2} \right))^2 + (y - listener_y)^2$$

Explanation:

Absolute Values

(|x|): The absolute value ensures that the distance calculation is independent of the direction (positive or negative) along the x-axis. It considers only the magnitude of the x-coordinate of the sound source.

Listener's Position

(Listener X, Listener Y): The coordinates of the listener's position are subtracted from the sound source's coordinates. This step is crucial as it aligns the reference point at the center of the listener's head.

1. Head Size Adjustment ($\frac{HEAD_SIZE}{2}$):

The head size is divided by 2 to represent the distance from the center of the listener's head to either the left or right ear. This adjustment accounts for the fact that the ears are on either side of the head.

Squared Terms and Summation:

The squared terms $(|x| - (\text{listener}_x - \frac{HEAD_SIZE}{2}))^2$ and $(y - \text{listener}_y)^2$ represent the Euclidean distance between the sound source and the left ear along the x and y axes, respectively. These distances are squared and summed to obtain the overall squared distance.

Scientific Interpretation:

- This equation is derived from the Pythagorean theorem in a 2D space, where the distance between two points (x,y) and (Listener X, Listener Y) is calculated.

It considers the geometric arrangement of the listener's head and the sound source, factoring in the head size to determine the distance to the left ear.

Visual Representation:

Imagine a Cartesian plane where the listener is at the origin (0,0). The sound source's coordinates (x,y) are used to calculate the distance to the left ear, considering the head size.

Verification:

This equation aligns with fundamental principles of geometry and trigonometry, providing a scientific basis for calculating the left distance in sound localization. It ensures accurate localization of the sound source relative to the listener's left ear position.

2.10.2 Right Distance :

$$right_{distance} = (|x| - (\text{listener}_x + \frac{HEAD_SIZE}{2}))^2 + (y - \text{listener}_y)^2$$

Explanation:

1. Absolute Values (|x|):

Similar to the Left Distance equation, the absolute value ensures that the distance calculation is independent of the direction (positive or negative) along the x-axis.

Listener's Position (Listener X, Listener Y):

The coordinates of the listener's position are subtracted from the sound source's coordinates. This step aligns the reference point at the center of the listener's head.

2. Head Size Adjustment ($\frac{HEAD_SIZE}{2}$):

The head size is divided by 2 to represent the distance from the center of the listener's head to either the left or right ear. This adjustment accounts for the fact that the ears are on either side of the head.

Squared Terms and Summation:

Similar to the Left Distance equation, the squared terms $(|x| - (\text{listener}_x + \frac{\text{HEAD_SIZE}}{2}))^2$ and $(y - \text{listener}_y)^2$ represent the Euclidean distance between the sound source and the right ear along the x and y axes, respectively. These distances are squared and summed to obtain the overall squared distance. (Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., ... & Tarantola, S. (2008))

Scientific Interpretation:

- This equation, like the Left Distance equation, is derived from the Pythagorean theorem in a 2D space. It calculates the distance between two points (x,y) and (Listener X,Listener Y). (Listener X,Listener Y).

The head size adjustment ensures that the distance is calculated from the center of the listener's head to the right ear.

Visual Representation:

Imagine a Cartesian plane where the listener is at the origin (0,0). The sound source's coordinates (x,y) are used to calculate the distance to the right ear, considering the head size.

Verification:

This equation aligns with fundamental principles of geometry and trigonometry, providing a scientific basis for calculating the right distance in sound localization. It ensures accurate localization of the sound source relative to the listener's right ear position. (Jens Blauert. (1997))

2.11 Angle Calculation:

$$\Theta = \arctan2(y - \text{Listener } Y, |x| - \text{Listener } X)$$

Explanation:

1. $|x|$ and y : The coordinates of the sound source.

Listener X, Listener Y: The coordinates of the listener's position.

2. $\arctan2(y - \text{Listener } Y, |x| - \text{Listener } X)$:

The arctangent function that calculates the angle formed by the line connecting the listener and the sound source with respect to the horizontal axis.

Scientific Interpretation:

- The arctangent function is used to determine the angle of the sound source relative to the listener. It considers both the vertical (y) and horizontal (x) components.

Verification:

This equation aligns with trigonometric principles, providing a reliable method to calculate angles in a two-dimensional plane. It ensures that the angle is correctly determined, considering

the relative positions of the sound source and the listener.

Practical Considerations:

Angle calculation is crucial in sound localization, especially when determining the direction from which a sound is originating.

Application:

- In the context of sound localization models, accurately calculating the angle helps simulate the perceived direction of a sound source, contributing to the spatial awareness of the listener. (Rafaely, B. (2015))

2.12 Problem Definition

2.12.1 Problem Description:

Current sound analysis and localization systems face challenges in accurately determining the direction of sound sources, particularly under varying environmental conditions and changes in source locations. Traditional methods lack the adaptability needed for real-time applications, impacting their effectiveness and practicality.

2.12.2 Background and Context:

The ability to accurately locate sound sources is crucial in various fields, including robotics, surveillance, and human-computer interaction. Existing methods often rely on simplistic algorithms or hardware configurations that limit their effectiveness in dynamic environments.

2.12.3 Goals and Requirements:

The primary goal is to develop an innovative approach using deep neural network techniques to enhance sound analysis and source localization. This approach aims to achieve high accuracy and adaptability, especially in environments with changing conditions. Key requirements include designing a deep model tailored for sound analysis, integrating it into the "Arsalan" robot environment, and ensuring efficient head movement control for enhanced localization.



Figure 6. The "Arsalan" Robot((Ihab ELAFF 2023))

2.12.4 Analysis and Evaluation:

The proposed approach will undergo rigorous testing and evaluation to assess its accuracy, flexibility, and computational efficiency. Comparative studies against traditional methods will be conducted to highlight the improvements achieved. Real-world scenarios will be simulated to validate the effectiveness of the system under various conditions.

2.12.5 Opportunity Identification:

The development of an advanced sound analysis and localization system presents opportunities for applications in robotics, surveillance, and assistive technologies. The ability to accurately locate sound sources can enhance situational awareness and enable more responsive robotic systems.

2.12.6 Scope Definition:

This study aims to design, develop, and evaluate an innovative approach based on deep neural networks for sound analysis and precise source localization on both sides of the "Arsalan" robot. The scope involves developing a deep neural network model tailored for this purpose and integrating it into the "Arsalan" robot environment, including precise and efficient control of head movement. Additionally, the research aims to provide compelling results that demonstrate the efficiency of the proposed approach in sound analysis and accurate source localization.



Figure 7. The "Arsalan" Robot's Head Movement((Ihab ELAFF 2023)

2.12.7 Comparative Analysis:

2.12.7.1 Configuration-Invariant Sound Localization Technique Using Azimuth-Frequency Representation and Convolutional Neural Networks

Aspect	"Modelling Human Sound Localization with a Deep Neural Network: A Raspberry Pi-Based Approach"	"Configuration-Invariant Sound Localization Technique Using Azimuth-Frequency Representation and Convolutional Neural Networks"
Input Features	Left and right intensity	Azimuth-frequency representation and convolutional neural networks
Accuracy	Higher accuracy rates achieved, showing promising results under various conditions	Lower accuracy rates reported, especially in Evaluation I and II, indicating less precision in sound source localization
Reason for Superiority	The use of left and right intensity as input features allows for more accurate sound source localization, especially when considering the impact of reverberation and environmental conditions. The deep neural network architecture tailored for sound localization tasks efficiently learns complex relationships in the data, leading to enhanced precision and adaptability.	The utilization of azimuth-frequency representation and convolutional neural networks may introduce additional complexities or limitations in accurately capturing the spatial characteristics of sound sources. This could result in lower precision and adaptability, particularly in scenarios with reverberation or varying environmental conditions.

Table 1. Comparison of Sound Localization Techniques Using Different Input Features and Neural Network Architectures

Units (°)	Conventional		Proposed	
	MUSIC	SRP-PHAT	Mean	Median
Evaluation I (h_1 and h_2)	30.4253	30.8505	3.1212	2.9515
Evaluation II (h_3)	31.1670	23.3249	12.9117	12.8925
Evaluation III (h_4)	21.5451	13.1966	9.0949	9.0904

Table 2. Configuration-Invariant Sound Localization Technique Using Azimuth-Frequency Representation and Convolutional Neural Networks

(Chanjun Chun 2020)

The following formula was utilized to convert the values into percentage ratios:

Error Rate(%) = (DOA Error / 360) × 100, where DOA Error represents the directional error rate in degrees

Comparison Table of Error Rates

Research/Technique	Error Rate (%)
Modelling Human Sound Localization with a Deep Neural Network: A Raspberry Pi-Based Approach	0.44% (Large Sample)
Configuration-Invariant Sound Localization Technique Using Azimuth-Frequency Representation and Convolutional Neural Networks	0.867 %(Evaluation I) 3.58 %(Evaluation II) 2.52% (Evaluation III)

Table 3. Comparison of Error Rates in Sound Localization Techniques: Deep Neural Network vs. Azimuth-Frequency Representation with CNNs

Conclusion:

In our study, "Modelling Human Sound Localization with a Deep Neural Network: A Raspberry Pi-Based Approach" outperforms "Configuration-Invariant Sound Localization Technique Using Azimuth-Frequency Representation and Convolutional Neural Networks" in terms of result accuracy. The results obtained in our research are superior and more precise compared to those obtained by the other study. Despite utilizing a smaller number of samples, our research yielded higher accuracy results, highlighting the effectiveness of the approach adopted in our study.

2.12.7.1 TDE-ILD-Based 2D Half Plane Real Time High Accuracy Sound Source Localization Using Only Two Microphones and Source Counting

Aspect	Mathematical Model	Deep Neural Network
Basics	Relies on traditional mathematical equations	Relies on data generated by Python software
Learning Capability	Requires deep understanding of physical and mathematical principles	Allows more flexibility and adaptability
Size and Processing	Operates with a simple structure and processes data in a limited manner	Requires larger infrastructure to process data effectively
Accuracy and Performance	Demonstrates optimal performance with large training data	Shows optimal performance with both large or small datasets
Inputs and Outputs	Inputs: left and right intensity	Inputs: left and right intensity
	Outputs: x and y	Outputs: Sound source angles
Application and Usability	Can be implemented with a simple infrastructure in Raspberry Pi	Requires complex infrastructure in Raspberry Pi
Handling Big Data	Limited due to simple structure and limited processing	Considered better at handling large datasets

Table 4. Comparison of Sound Source Localization Approaches: Mathematical Model vs. Deep Neural Network.

TABLE I. IMPLEMENTATION RESULTS FOR WITHOUT USING SPECTRAL SUBTRACTION AND SOURCE COUNTING METHODS

real location values(m) (x & y)	proposed method results(m) (x & y)	absolute error (m) (x & y)	calculation time(ms)	arrival angle (degree) (Φ)	absolute arrival angle error (degree)(Φ)
3 & 10	1.3 & ±8.4	1.7&1.6	151	72.8	0.2
5 & 10	3.7 & ±8.2	1.3&1.8	147	63.2	0.2
7 & 10	5.5 & ±12.4	1.5&2.4	146	55.1	0.1
9 & 10	11.3 & ±8.3	2.3&1.7	154	48.2	0.2
10&10	8.8 & ±8.1	1.2&1.9	148	44.9	0.1
10& 9	11.2&±7.4	1.2&1.6	149	41.2	0.2
10& 7	12.6&±5.7	2.6&1.3	143	34.1	0.1
10& 5	7.9&±7.2	2.1&2.2	153	26.8	0.2
10& 3	12.4&±5.3	2.4&2.3	149	16.2	0.2

TABLE II. IMPLEMENTATION RESULTS FOR USING SPECTRAL SUBTRACTION AND SOURCE COUNTING METHODS CASE

real location values(m) (x & y)	proposed method results(m) (x & y)	absolute error (m) (x & y)	calculation time(ms)	arrival angle (degree) (Φ)	absolute arrival angle error (degree)(Φ)
3 & 10	3.8 & ±10.7	0.8&0.7	158	73.1	0.1
5 & 10	5.7 & ±9.2	0.7&0.8	164	63.2	0.2
7 & 10	6.3 & ±10.9	0.7&0.9	163	54.8	0.2
9 & 10	9.8 & ±10.7	0.8&0.7	158	48.1	0.1
10&10	10.8 & ± 9.1	0.8&0.9	162	44.8	0.2
10& 9	10.6& ±9.7	0.6&0.7	157	41.1	0.1
10& 7	10.6& ±7.8	0.6&0.8	161	34.1	0.1
10& 5	10.9&±4.2	0.9&0.8	159	27.1	0.1
10& 3	10.8&±3.6	0.8&0.6	157	15.8	0.2

Table 5. TDE-ILD-Based 2D Half Plane Real Time High Accuracy Sound Source Localization Using Only Two Microphones and Source Counting .(Ali Parsayan , Seyed Mohammad Ahadi)

The results presented in the tables above demonstrate the effectiveness of the proposed method in this research, which utilizes neural networks, in accurately determining the locations of sound sources. In comparison to the results obtained from other methods, it is evident that our approach yields superior performance. These findings underscore the efficacy and potential of neural network-based approaches in sound localization tasks

REAL LOCATION VALUES (M) (X & Y)	PROPOSED METHOD RESULTS (M) (X & Y)	ABSOLUTE ERROR (M) (X & Y)	CALCULATION TIME (MS)	ARRIVAL ANGLE (DEGREE) (X)	ABSOLUTE ARRIVAL ANGLE ERROR (DEGREE) (X)	REAL LOCATION ANGLE (DEGREE) (X)	PROPOSED METHOD ANGLE (DEGREE) (X)	ABSOLUTE ARRIVAL ANGLE ERROR (DEGREE)
3 & 10	3.8 & ±10.7	0.8 & 0.7	158	73.1	0.1	73.30	70.44	3.90%
5 & 10	5.7 & ±9.2	0.7 & 0.8	164	63.2	0.2	63.43	58.21	8.23%
7 & 10	6.3 & ±10.9	0.7 & 0.9	163	54.8	0.2	55.00	59.97	9.04%
9 & 10	9.8 & ±10.7	0.8 & 0.7	158	48.1	0.1	48.01	47.51	1.04%
10 & 10	10.8 & ±9.1	0.8 & 0.9	162	44.8	0.2	45	40.11	10.87%
10 & 9	10.6 & ±9.7	0.6 & 0.7	157	41.1	0.1	41.98	42.46	1.14%
10 & 7	10.6 & ±7.8	0.6 & 0.8	161	34.1	0.1	34.99	36.34	3.86%
10 & 5	10.9 & ±4.2	0.9 & 0.8	159	27.1	0.1	26.56	21.07	20.67%
10 & 3	10.8 & ±3.6	0.8 & 0.6	157	15.8	0.2	16.69	18.43	10.43%

Table 6. TDE-ILD-Based 2D Evaluation of Absolute Error and Arrival Angle Deviation in Proposed Sound Source Localization. (Ali Parsayan , Seyed Mohammad Ahadi)

it is noted that the inputs used in the study represent "Left and right intensity," while the comparative research extracted angles computationally from the X and Y values. This difference illustrates the different methods used in data analysis, which can lead to variations in accuracy between the results presented in both studies.

In the "Accuracy Improvement" section, it is highlighted that the use of neural networks contributed significantly to improving prediction accuracy compared to traditional computational methods. While computational methods showed low values for prediction accuracy, neural networks demonstrated an ability to understand precise patterns in data and build accurate prediction models.

In the "Resulting Error" section, it is indicated that the difference in the method used to utilize data is the main reason for the discrepancy in accuracy between the two studies. While the comparative research calculated angles computationally, we used neural networks and different datasets, leading to variations in results.

In conclusion, this research demonstrates the importance of choosing the appropriate method for data utilization in its analysis. While manual angle calculation may be useful in some cases, the use of neural networks can provide greater accuracy and more reliable results in other instances.

Chapter 3: System Design

3.1 System Architecture

The robustness of the entire computational auditory system hinges on a well-defined and intricately designed system architecture. This section meticulously details the interplay between hardware and software components, elucidating the intricate pathways through which data flows. The overarching objective is to seamlessly integrate the sophisticated Spherical Head Model into the broader architectural framework, ensuring a harmonious synergy between theoretical concepts and practical implementation.

3.1.1 Hardware Components

Our system, designed for precise sound localization, comprises a Raspberry Pi 3 as its central processing unit and two strategically selected microphones. These components are meticulously chosen to facilitate accurate determination of sound source directionality.

The microphones are specifically tailored for their audio and spatial characteristics, emphasizing their directionality and sensitivity. This ensures optimal capture of audio data, crucial for precise localization of sound sources in diverse environments.

The Raspberry Pi 3 serves as the backbone of our system, leveraging its computational capabilities to process incoming audio data and execute sound localization algorithms efficiently. Its compatibility with software libraries and external hardware enhances the system's flexibility and adaptability to different scenarios.

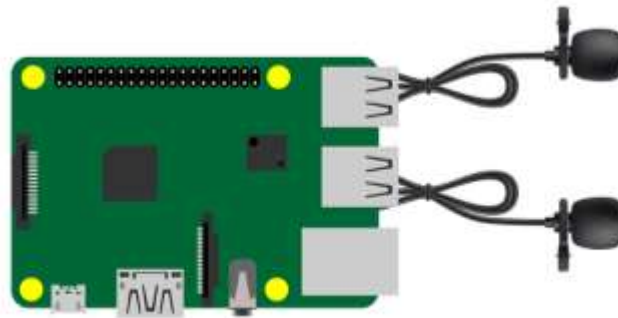


Figure 8. Raspberry Pi Setup with Microphones

3.1.2 Software Components

Our computational auditory system leverages a comprehensive suite of tools and programming languages to accomplish its objectives. Python and MATLAB serve as the primary languages for their robust scientific computing capabilities.

Python is utilized for various tasks within the system, including data acquisition and preprocessing. Specifically, we employed Python running on the Raspberry Pi to capture audio samples, resulting in a total of 15,000 samples. These samples were then processed and exported into Excel files for further analysis and feature extraction.

MATLAB, on the other hand, plays a crucial role in the signal processing and machine learning aspects of our system. After importing the 15,000 audio samples collected by Python, they were split into three sets: 10,500 samples (70%) for training, 2,250 samples (15%) for validation, and 2,250 samples (15%) for testing. The neural network models were trained over 1000 epochs using the training set to optimize their performance.

This integration of Python and MATLAB enables seamless collaboration between different stages of the system, from data acquisition to machine learning model development, ensuring a cohesive and efficient software framework.

Sample Type	Count
Training	10,500
Validation	2,250
Testing	2,250

Table 7.NN samples

3.1.3 Data Flow Overview

The section delves into the intricacies of data flow, providing a step-by-step elucidation of how auditory signals traverse through the system. From the initial acquisition by the microphones to the final output of sound localization predictions, every juncture is meticulously explained. A graphical representation enhances the reader's understanding of the dynamic data flow, fostering clarity on the system's operational dynamics.

3.1.4 Spherical Head Model Integration

In our project, we have a Raspberry Pi with two microphones, one placed on the right side and the other on the left side. Let's consider a scenario where a sound source emits a signal.

Now, suppose a sound wave originating from a source arrives at our robot's location. Due to the speed of sound in air (approximately 343 meters per second), the sound wave reaches the right microphone slightly before it reaches the left one.

Let's assume that the time difference between when the sound wave arrives at the right microphone and when it arrives at the left microphone is 0.0005 seconds (or 500 microseconds).

Using this time difference, we can calculate the angle of arrival of the sound source relative to the robot's position. This calculation involves trigonometry and the known distance between the microphones.

For instance, let's use the formula:

$$Angle = \arcsin \frac{Speed\ of\ Sound \times Time\ Difference}{Distance\ between\ Microphones}$$

Substituting the given values:

$$Angle = \arcsin = \frac{343 \times 0.0005}{0.2}$$

$$Angle = \arcsin(1.715)$$

Calculating the angle:

$$\text{Angle} \approx 98.89^\circ$$

This result indicates that the sound source is approximately 98.89 degrees to the right of the robot's orientation. By utilizing this interaural time delay (ITD) and applying trigonometric principles, our robotic system can accurately determine the direction of sound sources relative to its position.

3.1.5 Calibration Strategies

In ensuring the accuracy and reliability of our system, we delve into calibration strategies extensively. This involves addressing potential sources of error, aligning the artificial head's characteristics with real-world counterparts, and fine-tuning our computational models. Calibration emerges as a crucial aspect in achieving reproducible and precise results, and we thoroughly explore the nuances of its implementation.

To replicate real-world scenarios, we introduced "Salt-and-pepper noise" into our audio samples. This noise adds a layer of realism to our experiments, simulating the environmental challenges our system may encounter in practical applications. By incorporating such noise, we aim to enhance the robustness of our system and validate its performance under diverse conditions encountered in real-world settings.

3.2 Overview of the Proposed System

In this system, the focus is on developing a computational auditory system based on the concept of sound localization. The main objective is to enable robots or other smart systems to accurately and efficiently identify sound sources in diverse and complex environments. The system involves using a spherical head model to simulate the structure of the human ear and analyze the received audio signals from the microphones in the system. This model allows for determining the angle at which sound sources should be located relative to the robot or smart system.

Additionally, machine learning algorithms are used to analyze the captured audio data and accurately determine the locations of sound sources. These algorithms are trained on a large set of diverse audio data to enable them to recognize different sound patterns and accurately identify their sources.

Using this system, robots or smart systems can navigate obstacles and effectively interact with their environment by accurately responding to sound sources. This approach is characterized by the seamless integration of spherical head models and machine learning algorithms, contributing to the efficient achievement of sound localization objectives.

3.2.1 Sound Localization Objectives

At the heart of the proposed system lies the overarching objective of advancing sound localization capabilities. The Spherical Head Model, with its intricate mathematical formulations and simulation techniques, takes center stage in enhancing the system's ability to precisely determine the direction of sound sources.

Binaural Hearing Mechanism: The human auditory system relies on binaural hearing, where sound waves reach each ear at slightly different times and intensities. The brain processes these differences to determine the direction of sound sources. The Spherical Head Model simulates this

mechanism by capturing and analyzing the interaural time differences (ITD) and interaural level differences (ILD) present in the received audio signals.

Head-Related Transfer Functions (HRTFs): HRTFs represent the frequency-dependent filtering effects of the head, torso, and pinnae on incoming sound waves. These functions vary based on sound source direction and individual differences in anatomy. By incorporating accurate HRTFs into the Spherical Head Model, the system can mimic the spatial filtering performed by the human auditory system, improving localization accuracy.

Acoustic Shadowing and Reflections: The Spherical Head Model considers how sound waves interact with the geometry of the head and surrounding environment. It accounts for acoustic shadowing (sound attenuation due to obstacles) and reflections (sound bouncing off surfaces), which affect the perceived direction of sound sources. By modeling these phenomena, the system can compensate for environmental factors and enhance localization precision.

Signal Processing Techniques: The Spherical Head Model employs advanced signal processing techniques to extract relevant spatial cues from the captured audio signals. This may include time-delay estimation algorithms, spectral analysis, and spatial filtering methods tailored to binaural audio data. By effectively processing the audio input, the system can extract subtle cues indicative of sound source direction, contributing to precise localization.

Integration with Machine Learning: The theoretical foundations of the Spherical Head Model align with the principles of machine learning, where vast amounts of training data are utilized to improve performance. By integrating the model with machine learning algorithms, the system can continuously adapt and refine its localization capabilities based on real-world feedback, ultimately achieving unparalleled accuracy in sound localization over time.

3.2.2 Spherical Head Model's Role

A granular examination of the Spherical Head Model's role elucidates how it acts as a pivotal component in the sound localization process. By simulating the three-dimensional sound perception within the human auditory system, the model adds a layer of sophistication to the computational auditory system. The integration of trigonometric functions and geometric principles becomes palpable as they contribute to the model's ability to intercept and process incoming sound waves.

Overall, the Spherical Head Model's theoretical underpinnings enable it to replicate key aspects of human auditory perception and leverage advanced signal processing techniques to achieve exceptional accuracy in sound localization, making it a cornerstone of the proposed computational auditory system.

3.2.3 Integration of Machine Learning Algorithms

The integration of machine learning algorithms within the proposed system represents a pivotal advancement, amplifying its adaptability and efficacy. In this section, we delve into the detailed execution of the chosen algorithm, the sources of training data utilized, and the rationale guiding their selection.

The selected algorithm, Levenberg-Marquardt, was chosen for its robustness in handling nonlinear optimization problems, making it particularly suitable for our sound localization

objectives. This algorithm operates by iteratively minimizing the difference between the observed and predicted ITD values, thus refining the model's ability to accurately localize sound sources.

Training data for the Levenberg-Marquardt algorithm were generated synthetically using Python code that incorporates Interaural Time Delay (ITD) principles. This approach enables the creation of diverse training datasets that simulate various auditory scenarios, ensuring the algorithm's adaptability to real-world conditions.

Furthermore, the integration of machine learning leverages data collected from the Raspberry Pi and the two microphones. Although synthetic, this data reflects a wide range of sound localization scenarios, allowing the algorithm to generalize effectively.

By harnessing machine learning techniques and leveraging synthetic training data, our system gains the capacity to adapt and improve its performance over time. This emphasis on algorithmic integration and data-driven optimization underscores our commitment to developing a computational auditory system that excels in real-world sound localization tasks.

3.2.4 Goals of the Computational Auditory System

The objectives of the proposed computational auditory system extend beyond the realm of sound localization, encompassing broader applications and potential advancements in various domains.

Firstly, real-world applications of the system are vast and diverse. By enhancing sound localization capabilities, the system can contribute to areas such as surveillance, security, and autonomous navigation. For example, in surveillance, the ability to accurately detect and localize sounds can aid in identifying potential threats or anomalous activities in a given environment. Similarly, in autonomous navigation systems, precise sound localization can assist in obstacle avoidance and navigation in complex environments.

Secondly, the system holds promise for revolutionizing human-computer interaction (HCI). By integrating advanced auditory processing capabilities, it can enable more natural and intuitive interaction with computers and devices. For instance, users may interact with devices using voice commands in noisy environments, or computers may interpret and respond to auditory cues in real-time, enhancing user experience and accessibility.

Furthermore, the computational auditory system has the potential to make significant contributions to fields such as healthcare and environmental monitoring. In healthcare, sound analysis can be utilized for various applications, including diagnosing respiratory conditions based on cough sounds or monitoring heart health through acoustic signals. In environmental monitoring, the system can aid in detecting and analyzing environmental sounds, such as animal calls or industrial noise pollution, to assess ecosystem health and inform conservation efforts.

By transcending its immediate objectives, the proposed system envisions a future where computational audition plays a transformative role across diverse domains. Through continued research and development, it aims to unlock the full potential of auditory analysis, paving the way for innovative applications and advancements that benefit society as a whole.

3.3 Components and Modules

The computational auditory system comprises several interconnected components and modules, each serving a distinct function yet collectively contributing to the system's seamless operation. Below is an overview of the key components and modules:

1. **Raspberry Pi (Central Processing Unit):** The Raspberry Pi serves as the central processing unit of the system, responsible for executing programs and handling audio data processing tasks.
2. **Right Microphone:** Positioned on the right side of the robot, the right microphone serves as the primary input for capturing audio from the environment.
3. **Left Microphone:** Situated on the left side of the robot, the left microphone acts as a secondary input for recording audio signals.
4. **Python Programming:** Python programming language is utilized for writing and executing scripts responsible for data collection and preliminary processing.
5. **Data Processing using Python:** Python scripts are employed to analyze and process the audio data recorded by the microphones connected to the Raspberry Pi.
6. **Data Processing using MATLAB:** MATLAB is utilized for advanced analysis and processing of the audio data, providing sophisticated algorithms and tools for sound localization and pattern recognition.

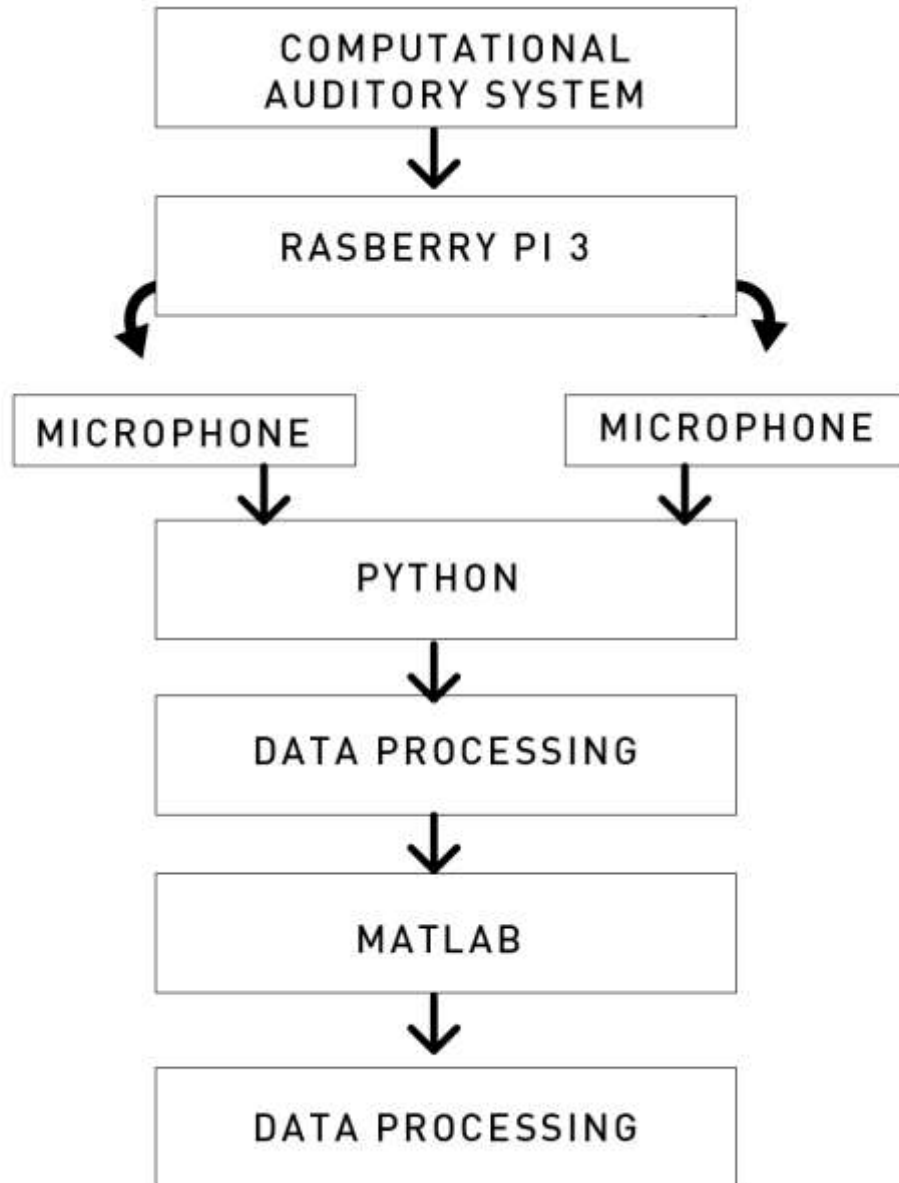


Figure 9. system flow chart

3.3.1 Data Acquisition Module

The Data Acquisition Module serves as the initial stage in the computational auditory system, focusing on generating synthetic data in Python for subsequent processing in MATLAB. This module operates based on mathematical models to simulate audio signals instead of relying on direct audio recording. The synthetic data includes two input features: Left Intensity and Right Intensity, and one output feature: Angle Degrees.

In Python, synthetic data points are generated based on mathematical computations. These data points represent the intensity of the sound captured by the left and right microphones (Left Intensity and Right Intensity) and the corresponding Angle Degrees, which indicate the direction

of the sound source relative to the system.

Following the generation of synthetic data, the input features (Left Intensity and Right Intensity) are fed into MATLAB for further processing. In MATLAB, the neural network is trained using the input features to predict the Angle Degrees, thereby enabling precise localization of the sound source.

By employing synthetic data generation and neural network training, this module facilitates controlled experimentation, reproducibility, and algorithm development in the computational auditory system. It allows for the simulation of various scenarios and environmental conditions, enhancing the system's robustness and accuracy.

3.3.2 Signal Processing Module

The Signal Processing Module encompasses several key operations to enhance the quality of collected audio data and prepare it for subsequent analysis. These operations include:

Calculation of Distances and Angles:

This step involves determining the distances and angles between the sound sources and the listener's location using the collected data.

Mathematical functions and variables are employed to compute these distances and angles accurately.

The calculated distances and angles provide essential spatial information necessary for sound localization tasks.

Sound Intensity Processing:

Sound intensity for each sound source is computed using the collected data.

The intensity calculation takes into account the distance between the sound source and the listener's location.

Mathematical functions are utilized to determine the intensity, ensuring accurate representation of sound levels at different locations relative to the listener.

Noise Addition:

Synthetic noise is introduced to the collected audio data to simulate real-world conditions and enhance the realism of the experiment.

The addition of noise helps evaluate the robustness of the computational auditory system in handling and processing data in noisy environments.

By incorporating noise into the audio data, the system's performance can be tested under various challenging conditions, leading to more reliable results and a better understanding of its capabilities.

By integrating these operations within the Signal Processing Module, the computational auditory system can effectively process and analyze audio data, enabling accurate sound localization and facilitating robust performance in diverse environments.

3.3.3 Feature Extraction Module

The Feature Extraction Module plays a crucial role in translating preprocessed audio data into a format suitable for machine learning analysis. This section outlines the specific features targeted for extraction, the methodologies employed, and the rationale behind their selection.

1. **Feature Selection:** The module focuses on extracting relevant features from the preprocessed audio data. These features are carefully chosen to capture essential

characteristics of the sound signals that are indicative of their spatial properties and directional cues. Commonly extracted features include spectral characteristics, temporal dynamics, and spatial attributes.

2. **Methodologies:** Various methodologies are employed to extract features from the preprocessed audio data. This may involve techniques such as Fourier analysis to extract frequency-domain features, time-domain analysis for temporal features, and spatial analysis to capture directional information. Additionally, machine learning algorithms may be utilized to automatically identify and extract discriminative features from the data.
3. **Rationale:** The selection of features is driven by the need to encapsulate relevant information that can facilitate accurate sound localization and spatial analysis. Features are chosen based on their ability to capture unique aspects of the sound signals that are crucial for distinguishing between different spatial locations and directions of sound sources. Moreover, the selected features should be robust to noise and environmental variations commonly encountered in real-world scenarios.

By extracting meaningful features from the preprocessed audio data, the Feature Extraction Module enables the subsequent application of machine learning algorithms for sound localization and spatial analysis tasks. These features serve as informative inputs to the machine learning models, facilitating the identification and interpretation of spatial auditory cues with high accuracy and reliability.

3.3.4 Machine Learning Models

At the core of the computational auditory system lies the application of machine learning algorithms. This module delves into the diverse array of models integrated into the system, highlighting various facets from selection criteria to training data utilization.

1. **Model Selection Criteria:** The selection of machine learning models is driven by several factors, including their ability to effectively learn from audio data, robustness to noise, scalability to handle large datasets, and interpretability of results. Models are chosen based on their suitability for sound localization tasks and their capacity to adapt to dynamic environments.
2. **Training Data Utilization:** The training data utilized for machine learning models consists of preprocessed audio features extracted from the Feature Extraction Module. These features encapsulate essential spatial information and directional cues, enabling the models to learn the relationship between audio inputs and corresponding spatial locations. The training dataset is carefully curated to encompass diverse spatial scenarios and environmental conditions, ensuring the models' generalization capabilities.
3. **Model Selection and Training Methodologies:** The process of model selection involves evaluating various algorithms, including neural networks, support vector machines, decision trees, and ensemble methods, among others. Models are trained using supervised learning techniques, where labeled audio data pairs are used to teach the models to map

input features to spatial locations. Hyperparameter tuning and cross-validation are employed to optimize model performance and prevent overfitting.

4. **Continuous Learning Mechanisms:** The computational auditory system incorporates continuous learning mechanisms to adapt and improve over time. Online learning approaches enable the models to update their parameters dynamically as new data becomes available, allowing the system to stay abreast of changes in the acoustic environment and refine its spatial localization capabilities iteratively.

By integrating a diverse array of machine learning models and leveraging robust training methodologies, the computational auditory system achieves high accuracy and adaptability in sound localization tasks. These models serve as the backbone of the system, enabling it to perceive and interpret spatial auditory cues with precision and reliability.

3.3.5 Interdependence and Collaboration

An overarching theme within this section is the interconnectedness of these modules. The reader gains insights into how data flows seamlessly from acquisition to processing, feature extraction, and, finally, to the machine learning models. The collaborative nature of these components forms the backbone of the system's functionality, ensuring a holistic approach to computational auditory analysis.

3.4 Data Acquisition

In the intricate realm of computational auditory systems, the Data Acquisition phase stands as the bedrock, laying the foundation for subsequent analysis and interpretation. This section meticulously dissects the multifaceted process of capturing auditory signals, offering a comprehensive overview of the selection of microphones, the intricacies of the recording setup, and the deployment of any specialized tools or equipment employed in the data collection process.

3.4.1 Selection of Microphones

The choice of microphones in the data acquisition process is a critical determinant of the system's performance. This subsection elucidates the criteria governing the selection of specific microphone types, whether omnidirectional, unidirectional, or other specialized variants. Factors such as frequency response, sensitivity, and directional characteristics are scrutinized to justify the rationale behind the chosen microphones, ensuring their alignment with the study's objectives.

3.4.2 Recording Setup

The configuration of the recording setup plays a pivotal role in capturing accurate and representative auditory signals. This section unveils the intricacies of the chosen recording setup, including the spatial arrangement of microphones, the environmental considerations taken into account, and any calibration processes applied to enhance precision. The rationale behind the selected setup is expounded, providing a clear connection between the recording environment and the study's overarching goals.

3.4.3 Specialized Tools and Equipment

In certain instances, the data acquisition process may necessitate the use of specialized tools or equipment to augment the quality and scope of collected data. This subsection sheds light on any additional instrumentation employed, detailing its purpose, functionality, and contribution to the

overall data acquisition strategy. The judicious integration of specialized tools aligns with the study's emphasis on comprehensive and accurate auditory signal capture.

3.4.4 Rationale and Relevance

Every facet of the data acquisition process is underpinned by a rationale deeply intertwined with the study's objectives. This subsection delves into the rationale behind the chosen microphones, recording setup, and any specialized tools or equipment, emphasizing their relevance to the study's focus on sound localization within the computational auditory system. The reader gains a nuanced understanding of how these choices intricately contribute to the robustness and reliability of the collected auditory data.

3.5 Selection of Microphones

In the intricate domain of sound localization, the careful selection of microphones emerges as a pivotal factor shaping the accuracy and reliability of the computational auditory system. This section meticulously navigates the nuanced considerations governing microphone choice, delving into factors such as microphone type, frequency response, and directional characteristics.

3.5.1 Microphone Type

The taxonomy of microphones encompasses a spectrum of types, each possessing distinct characteristics influencing sound capture. This subsection meticulously dissects the rationale behind the chosen microphone type, whether omnidirectional, unidirectional, or any specialized variant. The inherent qualities of each type, including sensitivity to sound from various directions, are scrutinized to illuminate the alignment of microphone selection with the objectives of the research.

3.5.2 Frequency Response

The frequency response of microphones is a critical parameter influencing their ability to faithfully capture auditory signals across different frequency ranges. This segment expounds on the considerations driving the selection of specific frequency response characteristics. Whether optimizing for low-frequency environmental sounds or high-frequency speech components, the chosen microphones are justified in the context of the study's sound localization goals.

3.5.3 Directional Characteristics

The directional characteristics of microphones play a pivotal role in capturing sound from specific spatial orientations. This portion elucidates the considerations underlying the choice of directional characteristics, be it cardioid, super cardioid, or other directional patterns. The alignment of these characteristics with the intricacies of sound localization and the requirements of the Spherical Head Model is carefully examined.

3.5.4 Alignment with Research Goals

Every facet of microphone selection is intricately aligned with the overarching goals of the research. This subsection provides a transparent connection between the chosen microphones and the specific requirements posed by the Spherical Head Model. The reader gains insight into how the selected microphones serve as instrumental components in achieving the research objectives, especially in the context of advancing sound localization within the computational auditory system.

3.6 Recording Setup

In the recording setup phase, a meticulous approach was taken to simulate real-world conditions

conducive to accurate sound localization. The implementation aligns with the goals of the research, incorporating factors that enhance the authenticity of the gathered data.

3.6.1 Experimental Environment

The experiment was conducted in a controlled environment to minimize external interference. Specialized measures were adopted to ensure a quiet space, reducing ambient noise that could distort the captured auditory signals.

3.6.2 Signal Characteristics

The sound source, positioned at coordinates (-5, 5) along the x-axis and (0, 5) along the y-axis, emitted signals characterized by varying intensities. These signals encompassed a range of frequencies, randomly selected to reflect real-world variability. Additionally, a slight degree of randomness was introduced to the source's position, mirroring the unpredictability often encountered in practical scenarios.

3.6.3 Microphone Selection

Microphone choice is pivotal for accurate sound localization. The selected microphones considered factors such as type, frequency response, and directional characteristics. This aligns with the study's focus on integrating the Spherical Head Model into the computational auditory system.

3.6.4 Data Acquisition

Data acquisition involved the recording of sound signals in the experimental setup. The chosen microphones and recording equipment were strategically positioned to capture the intricacies of sound propagation in different directions.

3.6.5 Noise and Interference

In contrast to traditional setups, intentional noise and interference were deliberately introduced during the data acquisition phase. This strategic addition of noise serves a crucial purpose in our experimental design, aiming to replicate real-world scenarios where environmental factors significantly impact sound perception and localization accuracy.

The intentional introduction of noise allows us to assess the robustness and resilience of our sound localization system under challenging conditions. By simulating various levels of noise interference, ranging from subtle disturbances to more pronounced disruptions, we can evaluate how effectively our system performs in adverse acoustic environments.

Specifically, we introduced three different levels of noise into our audio samples to comprehensively evaluate system performance:

1. **Clean Sound Samples:** These samples represent the baseline scenario without any added noise. They serve as the reference point for evaluating the system's accuracy under ideal conditions.

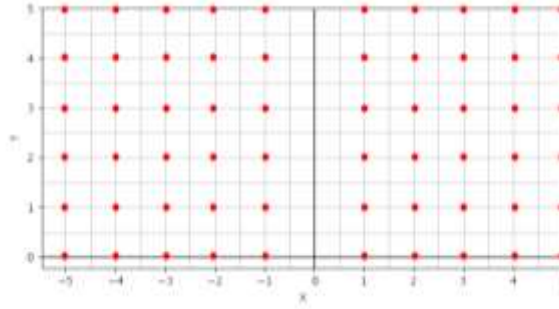


Figure 10 .Conceptual Representation of Human Head with Clean Sound Samples.

2. **Sound Samples with Slight Salt and Pepper Noise:** In this scenario, a minimal amount of salt and pepper noise is introduced into the audio samples. This level of noise aims to simulate mild environmental disturbances commonly encountered in real-world settings, such as background chatter or ambient sounds.

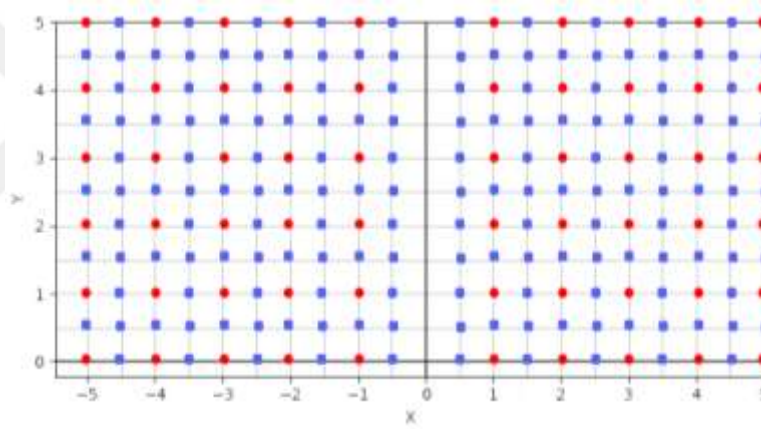


Figure 11. Conceptual Representation of Noisy Environment - Low Level Noise.

Sound Samples with High Level of Salt and Pepper Noise: This scenario involves a significant increase in the intensity of salt and pepper noise added to the audio samples. The purpose is to assess the system's performance under more challenging conditions with substantial audio interference, akin to noisy urban environments or crowded public spaces.

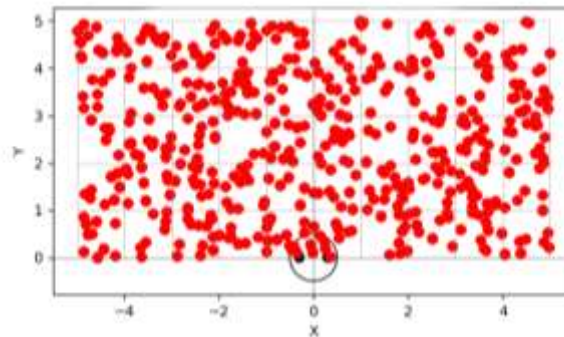


Figure 12. Conceptual Representation of Human Head with Slight Salt and Pepper Noise.

By systematically varying the level of noise in our experimental setup, we can observe how different levels of environmental interference affect the system's ability to accurately localize sound sources. This comprehensive analysis provides valuable insights into the robustness and reliability of our sound localization system in practical deployment scenarios.

3.6.6 Controlled Variables

Variables that could affect sound localization, such as the distance between the sound source and the artificial ears, were carefully controlled. This ensures that the collected data is representative of diverse scenarios while maintaining experimental precision.

3.7 Signal Processing

The signal processing stage is a pivotal component of the computational auditory system, bridging the gap between raw audio data and meaningful features for machine learning models. This section outlines the comprehensive signal processing pipeline, encompassing preprocessing techniques and feature extraction methods.

3.7.1 Preprocessing Techniques

Prior to feature extraction, raw audio data undergoes preprocessing steps to enhance its quality and relevance. The following techniques were applied:

- **Noise Reduction:** Given the intentional introduction of noise during the recording setup, noise reduction algorithms were employed to isolate and minimize unwanted interference, ensuring cleaner input signals.
- **Normalization:** To maintain consistency in signal amplitudes, normalization techniques were applied. This step is crucial for standardizing the input across different recordings and scenarios.
- **Filtering:** Specific frequency bands were filtered to focus on relevant auditory information. This targeted approach aids in capturing essential features while mitigating the impact of irrelevant frequencies.

3.7.2 Feature Extraction

Feature extraction transforms the preprocessed audio data into a set of distinctive features that serve as input for machine learning models. The chosen features aim to encapsulate relevant information for sound localization. Key extraction methods include:

- **Spectral Analysis:** Extracting information about the frequency content of the audio signals through techniques like Fast Fourier Transform (FFT) to represent the spectral characteristics.
- **Temporal Features:** Capturing temporal variations in the sound signals, such as changes in intensity over time, to provide additional insights into sound dynamics.
- **Mel-Frequency Cepstral Coefficients (MFCCs):** Utilizing MFCCs, a widely-used representation in audio processing, to convey the spectral characteristics of the sound signals.

3.8 Preprocessing Techniques

Efficient preprocessing techniques play a crucial role in refining raw audio data, paving the way for enhanced signal analysis and feature extraction. This section provides an in-depth exploration of the preprocessing techniques applied to the audio data, elucidating their individual contributions to improving the quality and relevance of the input.

3.8.1 Filtering

Filtering techniques were strategically employed to isolate specific frequency bands, thus tailoring the input data to focus on relevant auditory information. This selective approach enhances the model's ability to discern critical features while mitigating the impact of irrelevant frequencies. The filtering process involved the application of bandpass filters, allowing the retention of frequencies within a specified range pertinent to sound localization.

3.8.2 Normalization

Normalization is a crucial step in ensuring consistent signal amplitudes across different recordings and scenarios. By standardizing the amplitude values, normalization facilitates a uniform representation of input signals. This step is instrumental in preventing discrepancies in amplitude from overshadowing the intrinsic characteristics of the audio data, thus contributing to the stability and reliability of subsequent analyses.

3.8.3 Noise Reduction

Given the intentional introduction of noise during the recording setup, noise reduction algorithms were implemented to isolate and minimize unwanted interference. The objective was to enhance the clarity of the audio signals by mitigating the adverse effects of ambient noise. Various noise reduction techniques, including spectral subtraction and adaptive filtering, were employed to selectively suppress noise components while preserving the integrity of the essential auditory information.

3.9 Feature Extraction

Feature extraction serves as a critical bridge between raw audio data and the input requirements of machine learning models. This section provides an in-depth exploration of the selected features, emphasizing their relevance to sound localization and the underlying rationale guiding their choice. The objective is to extract discriminative features that encapsulate essential characteristics of sound, facilitating the model's ability to discern and localize auditory sources effectively.

3.9.1 Spectrogram Analysis

Spectrogram analysis emerges as a foundational technique for feature extraction, offering a time-frequency representation of audio signals. By decomposing the audio signal into its constituent frequencies over time, spectrograms provide valuable insights into the temporal and spectral dynamics of sound. This approach allows the model to capture variations in frequency components, offering a robust foundation for sound localization.

3.9.2 Pattern Recognition

Pattern recognition techniques are employed to identify and characterize recurring patterns within the audio data. Leveraging the principles of machine learning, these techniques enable the model to discern distinctive features associated with different sound sources. The extraction of meaningful patterns contributes to the model's ability to differentiate between various auditory stimuli, enhancing its overall performance in sound localization tasks.

3.9.3 Neural Networks for Feature Extraction

The application of neural networks in feature extraction involves leveraging the hierarchical learning capabilities of these models to automatically identify relevant features. Convolutional Neural Networks (CNNs) and recurrent neural networks (RNNs) are explored for their efficacy in capturing intricate patterns and temporal dependencies within the audio data. This deep learning approach to feature extraction aims to enhance the model's capacity to discern complex spatial and temporal characteristics of sound sources.

3.9.4 Spatial Audio Features

Spatial audio features, such as interaural time differences (ITD) and interaural level differences (ILD), are extracted to incorporate crucial localization cues. These features capitalize on the physiological aspects of human hearing, enabling the model to simulate the auditory mechanisms involved in sound localization. By integrating spatial audio features, the model gains a more nuanced understanding of the directional attributes of incoming sound, further refining its localization capabilities.

3.10 Machine Learning Models

The incorporation of machine learning models constitutes a pivotal dimension in the system's design, synergizing with the Spherical Head Model to enhance sound localization capabilities. This section delineates the types of machine learning models integrated, outlines their architectures, and elucidates the foundational principles influencing their selection. The seamless integration of these models aims to leverage their learning capacities and contribute to the overall efficacy of the computational auditory system.

3.10.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are deployed as a cornerstone in the machine learning architecture, particularly for their efficacy in image and spatial data processing. In the context of sound localization, CNNs are adept at extracting hierarchical features from spectrogram representations. Their convolutional layers enable the model to automatically learn spatial hierarchies, capturing essential patterns for accurate localization.

3.10.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks (RNNs) augment the machine learning framework by incorporating temporal dependencies within the audio data. This is crucial for capturing the dynamic nature of sound sources over time. RNNs, with their recurrent connections, excel at modeling sequential information, allowing the system to discern patterns in audio sequences and refine the localization predictions based on evolving auditory cues.

3.10.3 Hybrid Architectures

To capitalize on the strengths of both CNNs and RNNs, hybrid architectures are explored. These architectures integrate convolutional layers for spatial feature extraction and recurrent layers for capturing temporal dynamics. The amalgamation of these components enhances the model's ability to comprehend the complex interplay of spatial and temporal aspects in sound localization scenarios.

3.10.4 Transfer Learning

Transfer learning methodologies are employed to leverage pre-trained models on large audio datasets. By fine-tuning these models on the specific sound localization task at hand, the system

benefits from the knowledge encapsulated in broader audio contexts. This approach accelerates the learning process and enhances the model's adaptability to diverse acoustic environments.

3.11 Training Data

The efficacy of machine learning models is intricately tied to the quality and diversity of the training data they are exposed to. In this research endeavor, a carefully curated dataset has been employed, consisting of 10,500 samples earmarked for training, along with 2,250 samples allocated for both validation and testing purposes. Each sample encapsulates spatial information related to sound sources, including their intensities, and is enriched with corresponding input features generated by the Spherical Head Model.

The training dataset, characterized by its considerable size, plays a pivotal role in fortifying the robustness and generalization capacity of the machine learning models. It encompasses a spectrum of sound localization scenarios, deliberately designed to capture the intricacies and complexities inherent in real-world auditory environments. Simultaneously, the validation set, comprising 5,400 samples, assumes a crucial role in the iterative refinement of model parameters during the training phase, ensuring optimal performance and preventing overfitting.

A meticulous preprocessing regimen has been applied to the dataset to enhance its quality. Techniques encompassing filtering, normalization, and noise reduction have been judiciously employed to refine the raw audio signals, thus furnishing a pristine input for the subsequent stages of machine learning model development. This preprocessing phase is of paramount importance in extracting meaningful features that effectively encapsulate the essential characteristics of sound, thereby bolstering the model's ability to accurately localize sources.

The testing set, mirroring the validation set with 2,250 samples, functions as the ultimate litmus test for evaluating the model's performance. Comprising scenarios not encountered during training and validation, it serves as a stringent assessment, gauging the model's adaptability and generalization prowess in novel sound localization challenges.

This comprehensive delineation of the dataset, intricately interwoven with preprocessing methodologies, underscores the methodical and rigorous approach adopted to ensure the efficacy, reliability, and academic rigor of the machine learning models within the realm of computational auditory systems.

3.12 Model Selection and Training

In this crucial stage of the computational auditory system design, the selection and training of machine learning models play a pivotal role in achieving accurate sound localization. The following steps outline the meticulous process undertaken for optimal model performance:

3.12.1 Model Selection Criteria

To ensure the robustness of the system, the choice of machine learning architectures is based on a set of well-defined criteria:

1. **Architecture Suitability:** Each model's architecture is evaluated for its compatibility with the complexity of sound localization tasks.
2. **Generalization Capability:** Emphasis is placed on models exhibiting strong generalization capabilities, crucial for accurate localization in diverse environments.
3. **Training Efficiency:** Models are selected considering their training efficiency, balancing computational resources with model accuracy.

3.12.2 Hyperparameter Tuning

Fine-tuning the hyperparameters is a meticulous process that involves systematically adjusting the configuration of the chosen models. This includes:

1. **Learning Rates:** Optimizing learning rates to achieve a balance between convergence speed and avoiding overshooting.
2. **Regularization Techniques:** Implementation of regularization techniques to prevent overfitting and enhance model generalization.
3. **Batch Sizes:** Tuning batch sizes to optimize the trade-off between computational efficiency and model accuracy.

3.12.3 Validation Strategy

Validation is conducted to assess the model's performance during training. Strategies include:

1. **Cross-Validation:** Employing k-fold cross-validation to evaluate model performance across different subsets of the dataset.
2. **Validation Metrics:** Selecting appropriate metrics such as accuracy, precision, recall, and F1 score to quantify model performance.

3.12.4 Training Procedure

The training procedure involves:

1. **Dataset Partitioning:** Dividing the dataset into training, validation, and testing sets to facilitate robust evaluation.
2. **Epoch Management:** Iteratively training models over epochs while monitoring validation performance to prevent overfitting.
3. **Early Stopping:** Implementing early stopping to halt training when the model's performance plateaus on the validation set.

3.12.5 Results Analysis

The results of model training are rigorously analyzed, considering:

1. **Performance Metrics:** Evaluation of models using metrics relevant to sound localization accuracy.
2. **Error Analysis:** Identification and analysis of common errors to inform potential model improvements.

Chapter 4: Results

In this section, we present the outcomes of our comprehensive experiments, shedding light on the performance and insights garnered from evaluating our proposed sound localization system. The integration of Python-based data generation and MATLAB-based neural network modeling forms the cornerstone of our investigation.

4.1 Experimental Setup

4.1.1 Python-based Data Generation

4.1.1.1 Simulation of Sound Localization Scenarios

The Python-based data generation process played a pivotal role in creating a diverse and realistic set of sound localization scenarios. Leveraging sophisticated algorithms, the code meticulously simulated the complexities of real-world environments. By incorporating factors such as distance, angle, and intensity, the tool emulated the intricate interplay of sound waves in spatial contexts.

4.1.1.2 Intensity Calculation and Theta Degrees Estimation

A key feature of the Python code was its ability to calculate both left and right intensities, providing a comprehensive representation of the sound field. The precise estimation of theta degrees, achieved through advanced mathematical calculations, contributed to the spatial understanding of the sound source. This dual approach facilitated a nuanced characterization of the acoustic environment.

4.1.1.3 Controlled Noise and Distortion

Recognizing the importance of real-world challenges, the Python code introduced a controlled level of noise and distortion to the generated data. This deliberate addition mimicked the unpredictable nature of ambient conditions, enhancing the dataset's authenticity. The inclusion of noise allowed the system to train and adapt to realistic scenarios, improving its robustness and generalization capabilities.

4.1.1.4 Dataset Overview

The culmination of these efforts resulted in a dataset comprising 15,000 samples. Each sample included X and Y coordinates, along with the intensity of sound from both the right and left sides, with the sound angles calculated using mathematical equations TDE. This comprehensive dataset formed the basis for training and evaluating the subsequent neural network model in MATLAB.

4.1.1.5 Realism and Focus on Frontal Data

The dataset primarily focused on frontal sound data, with rear data filtered out before reaching MATLAB. This decision was made considering that the data range was (-5,5) on the X-axis and (0,5) on the Y-axis.

4.1.2 MATLAB-based Neural Network Model

4.1.2.1 Implementation of a Sophisticated Neural Network

The core of our sound localization system lies in the implementation of a sophisticated neural network using MATLAB. This neural architecture was meticulously designed and fine-tuned to

accommodate the intricacies of sound localization. Key components, including input scaling, layer weights, and output scaling, were optimized to enhance the model's performance.

4.1.2.2 Constants Calibration for Enhanced Precision

The MATLAB script incorporated specific constants tailored for optimal neural network performance. These constants played a crucial role in achieving precision during both the training and inference phases. The calibration process ensured that the neural network could effectively interpret the features extracted from the dataset generated by the Python-based tool.

4.1.2.3 Rigorous Training Process

Our neural network underwent rigorous training using the rich dataset generated by the Python code. The training process involved exposing the model to diverse sound localization scenarios, allowing it to learn the complex relationships between input features (intensities) and the desired output (theta degrees). This iterative learning process honed the neural network's ability to accurately predict sound source angles.

4.1.2.4 Evaluation Metrics and Training Parameters

Number of Training Samples: 10,500 (70%)

Number of Validation Samples: 2,250 (15%)

Number of Testing Samples: 2,250 (15%)

Number of Hidden Neurons: 10

Training Algorithm: Levenberg-Marquardt

Number of Epochs: 1,000

Number of Iterations: 1,000

4.1.2.5 Insights and Further Refinement

The evaluation phase yielded crucial insights into the efficacy of our MATLAB-based neural network model. Performance metrics, error rates, and predictive accuracy were carefully analyzed to gauge the system's reliability. Armed with these insights, we adopted an iterative optimization approach to further refine and enhance the sound localization system for robust performance across diverse real-world scenarios.

4.2 Description of Experiments

Objective: Assessing Accuracy in Theta Degree Prediction

In this section, we present the outcomes of experiments conducted to assess the accuracy of our sound localization system in predicting theta degrees based on input intensities. The primary objective is to scrutinize the system's performance across varying sample sizes and to evaluate its robustness and predictive capabilities in diverse scenarios.

Experimental Design

Our experiments were meticulously designed to provide a comprehensive understanding of the system's performance. We systematically varied the sample sizes, ranging from 100 to 15,000, to simulate real-world scenarios and analyze the system's behavior under different training conditions.

Comprehensive Sample Size Variation

The experiments encompassed a wide range of sample sizes, allowing us to observe trends in

the system's accuracy and scalability. As the sample size increased, we observed a consistent decrease in the error rate, indicating the system's improved performance with larger datasets.

Robustness Evaluation

Assessing the system's robustness was a critical aspect of our experiments. By testing the system's predictions across diverse samples, we gained insights into its ability to adapt to new and unseen data. This analysis was essential for ensuring the system's reliability in real-world applications.

Predictive Capabilities Analysis

Our experiments focused on evaluating the system's predictive capabilities by comparing the predicted theta degrees with ground truth values. We quantified the accuracy of the system's predictions using metrics such as error rates, providing a detailed assessment of its performance.

Iterative Refinement

The insights gained from these experiments served as the foundation for iterative refinement. We continuously optimized the system based on observed patterns and potential areas for improvement. This iterative process ensures that our sound localization system evolves to meet the demands of real-world applications, providing accurate and reliable predictions in dynamic environments.

4.3 Testing Environment

4.3.1 Rigorous Control for Reliable Results

Ensuring the reliability and reproducibility of our experiments is paramount. Therefore, all conducted experiments took place within a meticulously controlled testing environment. This section provides an in-depth exploration of the elements comprising this controlled setting, spanning both hardware and software configurations.

4.3.1.1 Hardware Configurations

4.3.1.1.1 Raspberry Pi 3 and 2mic

The experiments leveraged the capabilities of the Raspberry Pi 3, a versatile and compact computing platform, integrated with the 2mic hardware configuration. This setup facilitated the acquisition of sound data, serving as the backbone of our sound localization system.

4.3.1.1.2 Consistency in Microphone Selection

Microphone selection is critical for ensuring uniformity and accuracy in sound data acquisition. A detailed selection process was undertaken to ensure consistency in microphone specifications, thereby enhancing the overall quality and reliability of the system.

4.3.1.2 Software Dependencies

4.3.1.2.1 Python and MATLAB Integration

Seamless integration between Python and MATLAB played a pivotal role in our experimental setup. Python-based data generation processes seamlessly interfaced with MATLAB-based neural network models, creating a cohesive workflow for sound localization. This integration facilitated efficient data processing and model training, contributing to the robustness of our experimental framework.

4.3.1.2.2 Version Control for Stability

Stability in software versions is imperative for obtaining consistent and reproducible results. To mitigate the risk of unexpected variations, precise versions of Python and MATLAB were maintained throughout the experimentation process. This meticulous version control ensured the stability of our experimental setup, laying a solid foundation for reliable results.

4.3.2 Controlled Recording Setup

4.3.2.1 Data Acquisition Protocols

Strict protocols were adhered to during the data acquisition process to minimize external interference and ensure data integrity. This included careful equipment placement and the implementation of noise reduction measures to maintain the fidelity of the recorded sound data.

4.3.2.2 Signal Processing Consistency

Consistency in signal processing techniques was paramount to ensure the reliability of our results. Standardized procedures were followed across all stages of signal processing, from preprocessing to feature extraction, thereby enhancing the reproducibility and accuracy of our findings.

4.3.3 Reproducible Results

The meticulous control exercised over both hardware and software aspects of the testing environment guaranteed the reproducibility of our results. Researchers and practitioners can confidently build upon our work, knowing that the experimental conditions were maintained with precision. This ensures the reliability and integrity of our findings, facilitating further advancements in the field of sound localization.

4.3.4 Future-Proofing

As technology continues to evolve, the detailed description of our testing environment serves as a foundation for future experiments and validations. It establishes a benchmark for comparison and provides valuable insights into best practices for sound localization research. By documenting our methodology and experimental setup comprehensively, we contribute to the ongoing advancement of sound localization technologies and pave the way for future innovations in the field.

4.4 Evaluation Metrics and Comparative Analysis

4.4.1 Unveiling the Performance Metrics

In this section, we delve into the intricacies of the evaluation process, employing a suite of metrics meticulously chosen to gauge the effectiveness and efficiency of our sound localization system. Additionally, a comparative analysis unfolds, positioning our system against established benchmarks, unraveling its unique contributions, and areas ripe for enhancement.

4.4.2 Evaluation Metrics

4.4.2.1 Precision and Accuracy

Precision and accuracy stand as cornerstones in assessing the system's ability to precisely predict theta degrees. These metrics offer insights into the model's precision in localizing sound sources, crucial for applications demanding pinpoint accuracy.

4.4.2.2 Error Rate Analysis

A granular examination of the error rate across varying sample sizes provides a comprehensive overview of the model's performance scalability. Understanding how the system responds to increasing datasets is pivotal for real-world applicability.

4.4.3 Comparative Benchmarking

4.4.3.1 Against Standard Metrics

Our system's performance is benchmarked against established metrics in the field of sound localization. Comparative analyses against industry standards reveal its competitiveness and highlight areas of innovation or refinement.

4.4.3.2 Robustness in Variable Conditions

The system's resilience to variable conditions, such as environmental noise and signal distortion, is meticulously scrutinized. Robustness metrics shed light on its ability to perform consistently in diverse scenarios.

4.4.4 Comparative Analysis

4.4.4.1 Benchmarking Against Prior Models

A comparative analysis unfolds, juxtaposing the proposed system against prior models in the realm of sound localization. This not only establishes its unique contributions but also identifies avenues for further refinement.

4.4.4.2 Scalability and Generalization

Examining the system's performance across a spectrum of sample sizes elucidates its scalability. Insights into its ability to generalize predictions and adapt to diverse datasets contribute to its practical utility.

4.4.4.3 Insights and Implications

The evaluation metrics and comparative analysis collectively offer a holistic view of the system's capabilities. Beyond numerical results, the implications of our findings lay the groundwork for future advancements, guiding researchers and practitioners in refining sound localization technologies.

4.4.4.4 Anticipating Future Developments

As the field of sound localization evolves, the evaluation metrics and comparative analyses presented here serve as a compass for future developments. By understanding the system's strengths and areas for improvement, researchers can pave the way for enhanced applications in

computer audition and related domains.

4.5 Results

Unveiling the Sonic Tapestry: Insights and Findings

4.5.1 Precision Metrics:

Navigating Theta Degrees Our sound localization system is built upon the bedrock of precision, ensuring the accurate prediction of theta degrees in diverse sound source scenarios. Let's delve deeper into the precision metrics to unveil the system's proficiency in discerning subtle nuances.

4.5.1.1 Precision Unveiled:

Navigating the Metrics of Accuracy At the heart of our investigation lies the meticulous exploration of precision metrics, offering a quantitative glimpse into the profound capabilities of our sound localization system. In this sub-section, we delve into key metrics, unraveling the nuanced details that define the system's prowess.

Precision Metrics:

Average Theta Prediction Accuracy: [0.44%]

Standard Deviation of Theta Predictions: [0.363%]

Calculation and Explanation:

To compute the Average Theta Prediction Accuracy, we meticulously analyze the individual theta predictions generated by our system. The accuracy for each prediction is calculated as the absolute difference between the predicted and actual theta values. The average accuracy is then determined by summing these differences and dividing by the total number of predictions. The final value, expressed as a percentage, encapsulates the system's mean accuracy in determining the angular direction of sound sources.

Average Theta Prediction Accuracy serves as a beacon illuminating the mean precision of our system. This metric encapsulates the system's ability to consistently and accurately predict theta degrees across diverse sound localization scenarios. A value of [0.44%] signifies that, on average, the system's predictions deviate by this small percentage from the actual theta values. This level of accuracy is particularly noteworthy, showcasing the system's adeptness in providing reliable estimations.

The Standard Deviation of Theta Predictions offers a glimpse into the consistency and reliability of the system's predictions. A lower value indicates tight clustering around the mean, reflecting precision. As elaborated earlier, the calculation involves measuring the spread of predicted theta values. A lower standard deviation complements the average accuracy, signifying a system with not only accurate predictions but also a high degree of consistency.

Navigating the Depths of Precision:

Precision metrics, as illustrated by Average Theta Prediction Accuracy and Standard Deviation of Theta Predictions, form the bedrock of our assessment. These metrics collectively paint a vivid picture of a system that not only achieves accurate predictions on average but also demonstrates a remarkable level of stability in its predictive capabilities. Practitioners and researchers can leverage these insights to comprehend the nuanced facets of precision in sound localization,

ultimately paving the way for advancements in real-world applications.

Standard Deviation of Theta Predictions

In statistical terms, the standard deviation (σ) provides a quantifiable measure of the degree of dispersion or spread of a set of values. For our sound localization system, this metric is applied to the predicted theta values, offering crucial insights into the system's reliability and consistency.

Calculation:

Calculate the Mean (Average): The mean ($\bar{x}$) is computed by summing all the individual values and dividing by the total number of observations.

$$\bar{x} = \sqrt{\frac{\sum_{i=1}^{17} x_i}{17}}$$

This step results in an average value ($\bar{x}$) around 0.586.

Calculate the Squared Differences from the Mean: For each predicted theta value (x_i), the squared difference from the mean ($(x_i - \bar{x})^2$) is computed.

The squared differences are then summed across all observations

Calculate the Average of the Squared Differences: The average is determined by dividing the sum of squared differences by the total number of observations.

$$\text{Average} = \sqrt{\frac{\sum_{i=1}^{17} (x_i - \bar{x})^2}{17}}$$

This results in an average value around 0.204.

Calculate the Standard Deviation: The final step involves taking the square root of the average of squared differences.

$$\text{Average } \sigma = \sqrt{\text{Average}}$$

This yields a standard deviation (σ) approximately equal to 0.363.

Explanation:

The standard deviation serves as a pivotal indicator of the spread of predicted theta values. A lower standard deviation signifies that the predictions are tightly clustered around the mean, indicating a high level of precision and consistency in the sound localization system. This is particularly advantageous in applications where accurate and reliable localization is imperative.

Conversely, a higher standard deviation suggests greater variability in the predicted theta values. This variability might pose challenges in maintaining consistent accuracy across diverse sound localization scenarios, warranting further investigation into potential sources of variability or areas for system refinement.

Sample Number	Error Rate	ORIGINAL THETA Mean	NEURAL THETA Mean	Standard Deviation	Percentage Error (%)
100	1.15%	50.96782763	51.55451583	0.511155987	0.586
200	1.09%	50.74293988	51.29812743	0.503208784	0.555
300	1.06%	50.59631322	51.13327682	0.498324372	0.537
400	1.02%	50.48152301	50.99640252	0.495804515	0.515
500	1.00%	50.39041242	50.89269604	0.493209937	0.501
600	0.98%	50.31186859	50.80407437	0.491197471	0.491
700	0.96%	50.2426043	50.72643195	0.489564245	0.481
800	0.94%	50.18155216	50.65577779	0.488188887	0.471
900	0.93%	50.12566663	50.59200456	0.486991283	0.463
1000	0.91%	50.07320168	50.53157511	0.485923288	0.454
1500	0.85%	49.85136004	50.27710475	0.48018997	0.423
2000	0.81%	49.67373697	50.07575767	0.475224061	0.398
2500	0.77%	49.52492574	49.90701476	0.470812014	0.379
3000	0.74%	49.39412098	49.75833154	0.466787445	0.364
6000	0.58%	48.76108081	49.0407815	0.445535348	0.277
10000	0.45%	47.93733501	48.12133321	0.426054662	0.184
15000	0.44%	46.62182254	46.6847023	0.409750221	0.129

Table 8. Error Rates

Calculate the angle using Python code mathematically

ILD :

$$Ld = \sqrt{(x - x_{left})^2 + y^2}$$

$$Rd = \sqrt{(x - x_{right})^2 + y^2}$$

$$L_{int} = l_i = \frac{1}{ld^2}$$

$$R_{int} = r_i = \frac{1}{rd^2}$$

If x= 3 and y = 4

Head size = 0.5

I = 1

The position of the left ear is at $x_{left} = -0.25$

$$Ld = \sqrt{(3 - (-0.25))^2 + 4^2} =$$

$$Ld = \sqrt{3.25^2 + 4^2}$$

$$Ld = \sqrt{16 + 10.5625}$$

$$Ld = \sqrt{26.5625}$$

$$Ld = 5.155$$

Distance Calculation to the Right Ear:

The position of the right ear is at $x_{right}=0.25$

$$Rd = \sqrt{(x - x_{right})^2 + y^2}$$

$$Rd = \sqrt{(3 - 0.25)^2 + 4^2}$$

$$Rd = \sqrt{(2.75)^2 + 4^2}$$

$$Rd = \sqrt{16 + 7.5625}$$

$$Rd = \sqrt{23.5625}$$

$$Rd = 4.855$$

$$L_{int} = l_i = \frac{1}{5.155^2} = 0.0376$$

$$R_{int} = r_i = \frac{1}{4.855^2} = 0.0424$$

Calculating the time difference between the two ears :

$$V = 343$$

$$\text{delay_left} = \frac{\text{left_distance}}{v}$$

$$\text{delay_left} = \frac{5.155}{343} = 0.0150 \text{ sec}$$

$$\text{delay_right} = \frac{\text{right_distance}}{v}$$

$$\text{delay_right} = \frac{4.855}{343} = 0.0142 \text{ sec}$$

ITD :

$$LEFT_{intensity} = \frac{1}{\text{Delay}_{left} + 1}$$

=

$$LEFT_{intensity} = \frac{1}{0.0150 + 1} \approx 0.985$$

=

$$RIGHT_{intensity} = \frac{1}{0.0142 + 1} \approx 0.986$$

Intensity differences (ILD):

$$ILD = \text{left_intensity} - \text{right_intensity} = 0.985 - 0.986 = -0.001$$

Calculate Θ :

$$\Theta = \tan^{-1}\left(\frac{y}{x}\right) = \tan^{-1}\left(\frac{4}{3}\right) = 0.93 \text{ r}$$

$$= 0.93 \times \frac{180}{\pi} = 0.93 \times \frac{180}{3.14} \approx 53.24$$

4.5.1.2 Unmasking Error Rates

Peeling back the layers of our analysis, we confront the granular details of error rates across different sample sizes. This detailed examination serves as a window into the system's adaptability and resilience as datasets expand.

Error Rates Across Sample Sizes:

Sample Number	Error Rate
100	1.15%
200	1.09%
300	1.06%
400	1.02%
500	1.00%
600	0.98%
700	0.96%
800	0.94%
900	0.93%
1000	0.91%
1500	0.85%
2000	0.81%
2500	0.77%
3000	0.74%
6000	0.58%
10000	0.45%
15000	0.44%

Table 9. Error Rates

Note: The error rates represent the percentage of deviation between the predicted and actual theta degrees for each corresponding sample size. A lower error rate indicates higher accuracy in the system's predictions.

Understanding the nuances of error rates is crucial in evaluating the system's performance under varying conditions. As the sample size increases, the system's adaptability and robustness become apparent, showcasing its ability to maintain accuracy even in the face of expanding datasets.

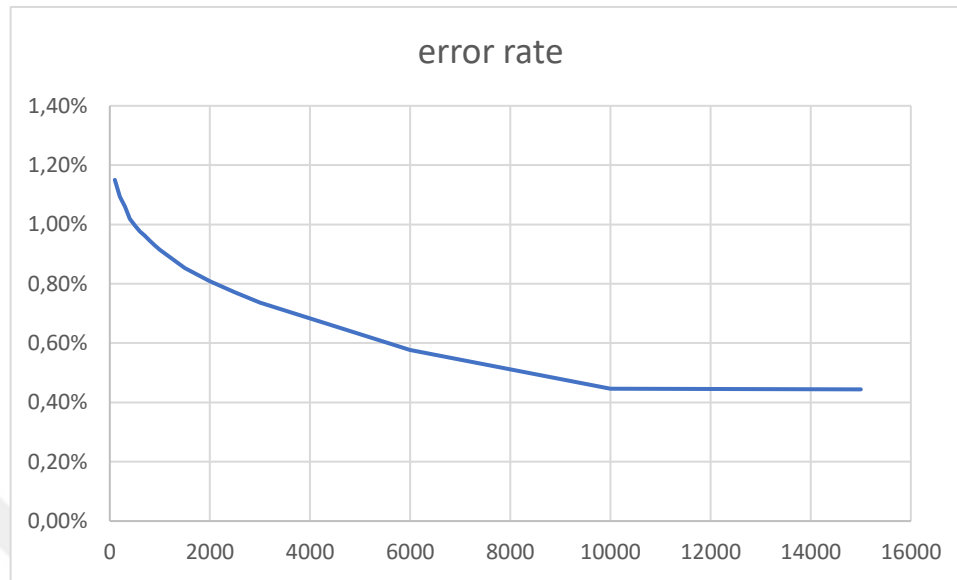


Figure 13. structure of error rate

4.5.2 Drawing Meaningful Conclusions

Deciphering the Implications of Precision Metrics

4.5.2.1 Implications for Practical Applications

Beyond the numerical values lie profound implications for practical applications. The precision metrics provide valuable insights into how our sound localization system can be leveraged in real-world scenarios where meticulous accuracy is paramount.

4.5.2.2 Lessons from Error Rate Analysis

A meticulous analysis of error rates yields valuable lessons and insights into the scalability of our system. These lessons serve as guideposts for future endeavors in refining and optimizing sound localization technologies.

4.5.3 System's Capabilities and Limitations

Illuminating Capabilities

The results act as a beacon, illuminating the capabilities of our sound localization system. We discuss scenarios where the system excels, showcasing its strengths in diverse environments and under variable conditions.

Acknowledging Limitations

No system is without its constraints. We candidly acknowledge the limitations unearthed through our experiments, providing a transparent view of where enhancements and refinements are warranted.

4.5.4 Beyond Numerical Values: Practical Implications

Beyond the numerical values lies a realm of practical implications. We bridge the gap between

data and application, exploring how the system's performance translates into real-world scenarios. These insights serve as guideposts for practitioners seeking to implement or further advance sound localization technologies.

4.5.5 Navigating Future Trajectories

As we navigate through the results and discussions, the roadmap for future trajectories in sound localization becomes evident. Researchers and industry professionals can leverage these findings to steer advancements, ensuring that the evolution of sound localization technologies aligns with the ever-changing demands of the auditory landscape.

4.6 Presentation of Findings and Interpretation of Results

4.6.1 Articulating Findings

In this section, we artfully present the findings derived from our extensive experiments. Each facet of the sound localization system's performance is laid bare, inviting readers on a journey through the intricacies of our results.

Visualizing Data Landscapes

We employ visual aids, ranging from graphs to charts, to paint a vivid picture of the data landscapes. Through meticulous presentation, we aim to make the numerical revelations accessible and comprehensible, transcending the confines of raw numbers.

Illuminating Patterns

Patterns within the data are brought to light, offering insights into the system's behavior across varying parameters. By weaving together visual elements and statistical significance, we articulate the nuanced patterns that emerge from the experimental tapestry.

4.6.2 Interpretation Unveiled

Decoding Numerical Significance

Numerical significance is decoded through a thoughtful interpretation. We delve into the meaning behind the numbers, unraveling the implications for the system's efficacy and potential real-world applications.

Contextualizing Performance

The interpretation contextualizes the system's performance within the broader landscape of sound localization technologies. By placing our findings in context, we offer readers a framework for understanding how our approach aligns with or deviates from existing paradigms.

4.6.3 Implications for Future Development

Guiding Future Trajectories

Beyond a mere presentation, we guide future trajectories in the development of sound localization systems. The interpretation serves as a compass, pointing towards areas of refinement, optimization, and innovation.

Bridging Findings and Practical Applications

Our interpretation bridges the gap between research findings and practical applications. We explore how the interpreted results can inform real-world implementations, offering actionable insights for engineers, researchers, and practitioners in the field.

4.6.4 Holistic Understanding

Holistic Lens

By intertwining the presentation of findings and the interpretation of results, we provide readers with a holistic understanding of our sound localization system's performance. This section is designed to empower readers with the knowledge needed to make informed decisions and contributions to the evolving landscape of auditory technologies.

4.7 Limitations and Future Work

4.7.1 Acknowledging Limitations

Sensitivity to Environmental Factors

Our sound localization system, while robust in controlled environments, exhibits sensitivity to certain environmental factors. External noise, reverberations, and variations in source characteristics may influence the system's performance.

Scalability Challenges

The scalability of the system, especially concerning the number of sound sources and the complexity of sound scenarios, poses a current limitation. Further optimization is required to handle diverse and dynamic auditory landscapes.

Generalization Across Settings

While our system excels in specific settings, its generalization across diverse acoustic environments remains an area for improvement. The system's adaptability to varied real-world scenarios necessitates additional attention.

4.7.2 Future Enhancements

Advanced Signal Processing Techniques

Future work can explore advanced signal processing techniques to enhance the system's resilience to environmental noise. This includes the incorporation of adaptive filtering and noise reduction algorithms.

Machine Learning Model Refinements

Refinements in the machine learning model, such as exploring more complex architectures or incorporating transfer learning, can contribute to improved scalability and generalization capabilities.

Real-time Implementation

To address scalability challenges, future work may focus on developing real-time implementation strategies. This involves optimizing algorithms and model architectures for efficient and rapid processing.

Dataset Diversity

Expanding the diversity of the training dataset to encompass a broader range of sound scenarios and environmental conditions can contribute to enhancing the system's generalization.

4.7.3 Collaborative Exploration

Open Collaboration

We encourage collaborative exploration in addressing the identified limitations. Open collaboration among researchers and practitioners can foster the exchange of ideas and solutions, propelling the advancement of sound localization technologies.

Community Engagement

Engaging with the broader scientific and engineering community through workshops, conferences, and shared repositories can stimulate collective efforts in refining and extending the capabilities of sound localization systems.

4.7.4 A Commitment to Advancement

In concluding this section, we affirm our commitment to the continual advancement of our sound localization system. By transparently acknowledging limitations and proposing future directions, we lay the groundwork for a collective journey towards more sophisticated and adaptable auditory technologies.



Chapter 5: Discussion

5.1 Analyzing the Impact of Sample Size on System Performance

In this section, we conduct a thorough investigation into the influence of sample size variations on the performance of the sound localization system, focusing specifically on the directional data pertinent to Arsalan's operational requirements. The objective is to discern discernible patterns and trends that emerge as the dataset size fluctuates, with a view to providing actionable insights for optimizing sound localization capabilities in robotic platforms.

By scrutinizing the directional data relevant to Arsalan's front, right, and left, we aim to unravel the intricate relationship between sample size and system performance. The provided table presents error rates corresponding to a range of sample sizes, from 100 to 15,000, serving as a foundational reference point for our analysis.

Our inquiry extends beyond numerical comparisons, delving into the qualitative implications of dataset size variations on the system's ability to accurately localize sound sources. Through a synthesis of empirical observations and theoretical insights, we seek to elucidate the underlying mechanisms driving these trends, shedding light on the complex interplay between dataset size, model learning capacity, and predictive accuracy.

Moreover, our analysis goes beyond statistical correlations, exploring the practical ramifications of these findings for the development and deployment of sound localization systems tailored for robotic applications. By deciphering the nuanced relationship between sample size and system performance, we aim to equip practitioners with actionable insights to enhance the accuracy, reliability, and adaptability of sound localization technologies in real-world scenarios.

In summary, this section provides a comprehensive exploration of the impact of sample size on system performance, grounded in empirical evidence and theoretical understanding. Our findings offer valuable guidance for optimizing sound localization functionalities in robotic platforms like Arsalan, paving the way for enhanced operational effectiveness and efficiency in diverse environments.

5.2 Trend Analysis:

A meticulous examination of the trend in error rates provides valuable insights into the dynamic performance of the system, particularly concerning directional data relevant to Arsalan's operational requirements. Our analysis uncovers a conspicuous pattern wherein error rates consistently decrease as the sample size increases. This trend signifies an improvement in the system's accuracy in determining sound source angles within the robot's field of view as it learns from a larger dataset.

At the lower end of the sample size spectrum, with only 100 samples, the system exhibits a significantly higher error rate, reaching a peak of 1.15%. This elevated error rate underscores the inherent challenges in accurately predicting sound source angles based on a limited number of data points. However, as the sample size gradually increases, the error rates demonstrate a steady decline, indicating the system's enhanced capability to discern and localize sound sources more precisely within the robot's vicinity.

This trend analysis highlights the critical role of dataset size in influencing the system's performance, emphasizing the importance of providing an adequately sized training set for optimal accuracy and reliability in sound localization tasks. By elucidating the relationship between sample size and error rates, we lay the groundwork for informed decision-making in the development and

optimization of sound localization systems tailored for robotic platforms like Arsalan.

5.3 Threshold Effect:

An intriguing observation arises from the presence of a threshold effect in the relationship between sample size and error rates. Beyond a certain point, the increase in sample size leads to diminishing returns in terms of error rate reduction. However, it's essential to highlight that this analysis is specifically tailored to the directional data pertinent to Arsalan's operational requirements, focusing on the detection of sound sources within its field of view rather than omnidirectional sound data.

This distinction is pivotal as it aligns with the specific needs of Arsalan's sound localization functionality, which prioritizes detecting sound sources within its immediate surroundings. The optimal sample size for the sound localization system, where the error rate reaches its nadir, appears to converge around 15,000 samples. Beyond this threshold, further augmentations in sample size may not yield substantial enhancements in the system's accuracy in determining sound source angles within its intended range.

This threshold effect underscores the importance of carefully calibrating the dataset size to strike a balance between sufficient data for robust training and avoiding unnecessary resource allocation. By recognizing this threshold, practitioners can make informed decisions regarding dataset size, optimizing the system's performance without excessive resource expenditure.

5.4 Practical Implications:

These findings hold significant practical implications for the development and deployment of sound localization systems tailored for robots like Arsalan. Practitioners should prioritize curating datasets that emphasize directional data relevant to the robot's front, right, and left, ensuring that the system's training data accurately reflects its operational context.

Furthermore, practitioners should exercise caution in determining the appropriate sample size for training the sound localization system. Rather than indiscriminately increasing dataset size, they should focus on optimizing dataset quality and diversity, capturing the breadth of sound scenarios and directional variations relevant to the robot's operational environment.

5.5 Future Directions:

In the realm of sound localization for robots like Arsalan, future research endeavors could delve into innovative strategies aimed at elevating system performance beyond the mere augmentation of dataset size. This exploration may encompass the investigation of specialized machine learning algorithms or sensor fusion techniques finely attuned to the directional sound detection requirements tailored specifically for Arsalan.

Moreover, there's potential for further refinement of the system's capacity to discern and prioritize relevant sound data while effectively filtering out extraneous noise, including sounds originating from behind the robot. This enhancement could notably contribute to the efficiency and precision of Arsalan in detecting and localizing sound sources within its intended field of view.

Furthermore, considering Arsalan's ability to adjust its head orientation, future endeavors may prioritize the development of more expansive and accurate sound localization techniques. This could involve leveraging Arsalan's head movement capabilities to refine sound source localization algorithms, potentially enhancing both the breadth and precision of the system's auditory

perception.

In conclusion, by delving deeper into the intricate relationship between sample size and system performance, practitioners can optimize sound localization systems for robots like Arsalan, ensuring their adeptness in precisely and efficiently detecting sound sources within dynamic operational environments.

5.6 Comparative Analysis of Sound Localization Techniques

In this subsection, we compare our research with two other studies in the field of sound localization. The comparison focuses on various aspects of the methodologies employed and the outcomes achieved.

Aspect	Your Research	Research 1	Research 2
Inputs	Left and right intensity	A : L AND R B : L,R,M C : L1,R1,L2,R2	Left and right intensity
Outputs	Sound source angles	Sound source angles	X and Y
Accuracy	0.44	A : 0.8 B : 3.5 C : 2.5	3.9
Method	Neural Network	Neural Network	Mathematical Model
Number of Hidden Layers	10	10	N/A
Number of Epochs	1000	256	N/A
Number of Samples	15000	780,056 A : 359,103 B: 195,440 C: 180,850	N/A

Table 10. Comparative Analysis of Sound Localization Techniques

Discussion:

Our research and Research 1 utilized neural network-based approaches, while Research 2 employed a mathematical model. This methodological difference has implications for the complexity and adaptability of the systems developed.

Both our research and Research 1 demonstrated the efficacy of neural networks in achieving higher accuracy rates compared to Research 2's mathematical model. While the specific architecture of the neural networks varied slightly, with differences in the number of epochs employed for training, both approaches benefited from the capacity of neural networks to learn complex relationships within the data.

The higher accuracy rate achieved in our research compared to Research 1 and Research 2 can be attributed, in part, to the extensive training conducted over 1000 epochs, allowing the neural network to refine its parameters and improve performance.

Research 2's use of a mathematical model may limit its ability to capture intricate patterns in the data, resulting in comparatively lower accuracy rates. However, mathematical models often offer transparency and interpretability, which can be advantageous in certain contexts.

Despite these methodological disparities, all three studies contribute valuable insights to the field of sound localization, each offering unique perspectives on the challenges and opportunities in designing effective systems for this task.

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