AudioPupil: A Low-cost Embedded Medical Device for Hearing Disorder Screening

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***Abstract*—Hearing impairment is an increasing global public health concern, yet traditional diagnostic methods are often inaccessible due to their high cost and complexity. This paper introduces a low-cost digital tool for objectively screening hearing disorders, utilizing a novel approach that leverages involuntary pupil dilation in response to sound as a comprehensive measure of auditory processing. The tool is designed for maximum user accessibility, featuring an intuitive interface, a detailed user manual, and cost-effective, high-precision sensors. A prototype has been successfully tested in a laboratory setting, demonstrating not only the system's potential for early detection and management of hearing impairments, particularly hyperacusis, but also its reliability and accuracy in capturing subtle auditory responses.**

***Index Terms*—auditory-pupillary response; hearing screening; cost-effectiveness; objective biomarkers.**

I. Introduction

Hearing loss is a significant global challenge, affecting approximately 1.57 billion individuals (20.3% of the global population) in 2019, with 430.4 million suffering from moderate to complete hearing loss. By 2050, this number is expected to rise by 56.1%, reaching 2.45 billion [1], [2]. This highlights the need for innovative diagnostic approaches.

Traditional hearing disorder diagnosis methods, like pure-tone audiometry, present barriers in cost, complexity, and accessibility, requiring specialized clinics and expensive equipment. Additionally, the lengthy nature of these tests deters busy individuals and burdens the elderly, highlighting the need for more accessible and user-friendly solutions [3]–[5].

Digital health technologies, such as mobile health applications and tele-audiology, offer promising solutions by leveraging smartphone capabilities and video conferencing for hearing assessments. Although their accuracy can be variable, these technologies improve accessibility and patient-friendliness, addressing barriers in traditional methods [6]–[9].

Our research hypothesizes that auditory function, particularly tinnitus and hyperacusis, can be effectively assessed through the pupillary dilation response (PDR) to auditory stimuli. The PDR, indicated by pupil size changes in response to sounds, may serve as a biomarker for these conditions [10], [11], offering insights into auditory system sensitivity, especially for hyperacusis. This approach aims to enhance auditory health assessment beyond traditional methods.

Central to our research is developing an innovative auditory evaluation system utilizing PDR for detailed analysis of tinnitus and hyperacusis. A machine learning model aims to extract precise biomarkers from PDR data, enhancing diagnostic accuracy. Leveraging cost-effective technologies and advanced machine learning, this approach seeks to transform the diagnosis and understanding of these conditions, particularly in resource-limited settings. Validating our PDR-focused system across diverse diagnostic scenarios remains a key challenge.

In summary, our research introduces a novel, low-cost digital tool for hearing disorder screening, leveraging the pupillary dilation response (PDR) as an objective biomarker. We demonstrate the tool's effectiveness in a controlled lab environment, showcasing its potential for accessible and early detection of auditory impairments.

II. Design Consideration

Nonvolitional Response in Auditory Assessment: Auditory Pupillary Response (APR) is a reliable, nonvolitional indicator of sound detection and discrimination. Studies [10], [11] suggest that APR has the potential to reflect auditory sensitivity in complex scenarios, making it a promising tool for those who struggle with traditional assessments, such as the elderly or individuals with cognitive or motor impairments.

Target Users and Application Scenarios: The system uses involuntary pupil response as a measurement indicator. This makes the test accessible to the elderly, children, and those with motor response impairments [10], [11]. In terms of application scenarios, the system plans to provide reference data for high-precision medical auditory testing and offers individuals concise and rapid hearing assessment reports.

Convenience and User-Friendliness: The system interface is user-friendly, with an intuitive layout and clear, easily readable labels. The user manual includes clear instructions and precautions for operation. This aims to make the system accessible to a wide range of users.

Cost-Effectiveness and Accuracy: The system uses cost-effective high-performance sensors, ensuring affordability without compromising on quality. The headphones and auditory stimuli used are professionally calibrated with specialized equipment, guaranteeing the accuracy of the auditory tests.

III. SYSTEM DESIGN

A. System Overview

Figure 1 shows the modular design of our auditory screening system. The software coordinates stimuli delivery and captures pupil response data simultaneously. After data acquisition, analysis ensures robust interpretation. The process starts with the subject receiving auditory or visual stimuli via headphones or display. Sensors capture involuntary responses, like pupil size changes detected by an IR camera, which are key in our assessment. The Control Panel synchronizes stimuli and data flow. During analysis, algorithms process the data to build a comprehensive profile of the subject's auditory health.

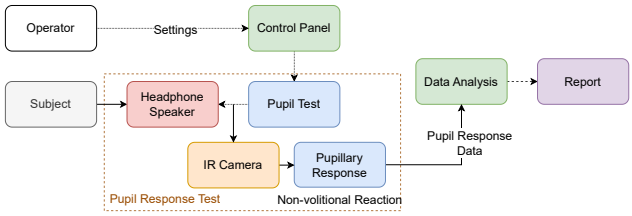
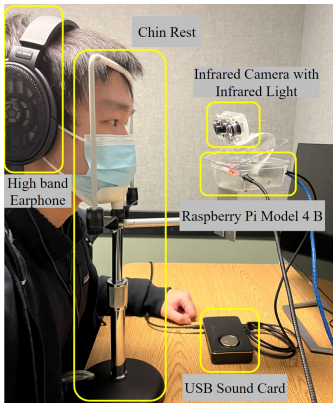
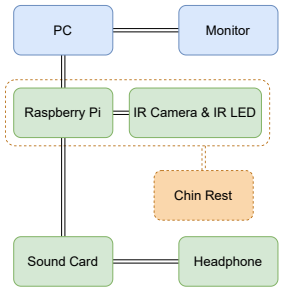


Fig. 1: The hearing disorder assessment system diagram



(a) Hardware components



(b) Hardware link

Fig. 2: Hardware graph

B. Hardware Design

Figure 2 details the primary hardware components of our system. These include a Raspberry Pi board [12], linked to an infrared camera with two infrared LED lights, and a USB sound card. The setup also features a 24-inch computer screen and an earphone. The Raspberry Pi serves as the central processing unit, recording raw data during tests. Its wireless connectivity simplifies setup, and storing and playing audio files directly on the Raspberry Pi ensures consistent auditory stimuli across different computers without recalibration.

An infrared camera and two infrared LED lights capture clear pupil images, particularly when pupil and iris colors are similar, allowing for precise measurements. A USB sound card is used to avoid background noise from direct headphone connections to the Raspberry Pi. A screen displays participant instructions, while earphones give auditory stimuli. The Chin Rest stabilizes the participant's head, ensuring accurate pupil data. The system is managed by a computer running data collection and analysis software.

Our hardware design introduces a cost-effective alternative to conventional eye-tracking systems, which, while offering high precision and extensive after-sales service with a high degree of customization, comes with a substantial price tag, typically over $10,000 [13]. In contrast, our system is designed to be economically viable, with a total cost of around $900, offers an intuitive user experience and includes analysis and processing components. Furthermore, its high component reusability makes it accessible to a wider research community and promotes sustainability.

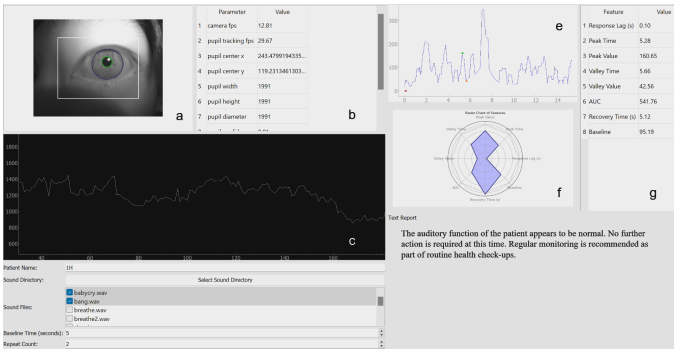


Fig. 3: UI (a) Real-time Pupil Tracking Image; (b) Parameter List; (c) Real-time Data Graph (d) Test Settings and Controls; (e) Feature Graphs for a Single Trial; (f) Radar Chart; (g) Feature Table; (h) Text Report.

C. Software Design

1) Interface Design

The software interface is designed to optimize the testing and analysis of the Auditory Pupillary Response (APR). The system's primary functions are categorized into three main areas: APR real-time display, APR testing setup, and APR analysis.

APR Real-time display: It displays real-time pupil screening (Fig. 3a). It also provides real-time tracking parameters, such as camera fps, pupil diameter, pupil center etc. (Fig. 3b) Additionally, users can click to view real-time plots of these parameters (Fig. 3c).

APR Testing Setup: Users can enter patient information, select sound files, and configure baseline time and the number of repetitions (Fig. 3d). Once the settings are confirmed, recording can begin.

APR Testing Result: It includes a feature graph showing detailed pupil responses for single trials, which helps analyze response patterns (Fig. 3e). Additionally, a radar chart visualizes key features such as peak time, valley time, etc., enabling quick comparison of different features (Fig. 3f). The feature table offers precise numerical values of various pupil response features for quantitative analysis (Fig. 3g). The text report will give an auditory evaluation summarization. (Fig. 3h).

2) Scoring Features The raw data from our hearing screening protocol is systematically captured in a structured

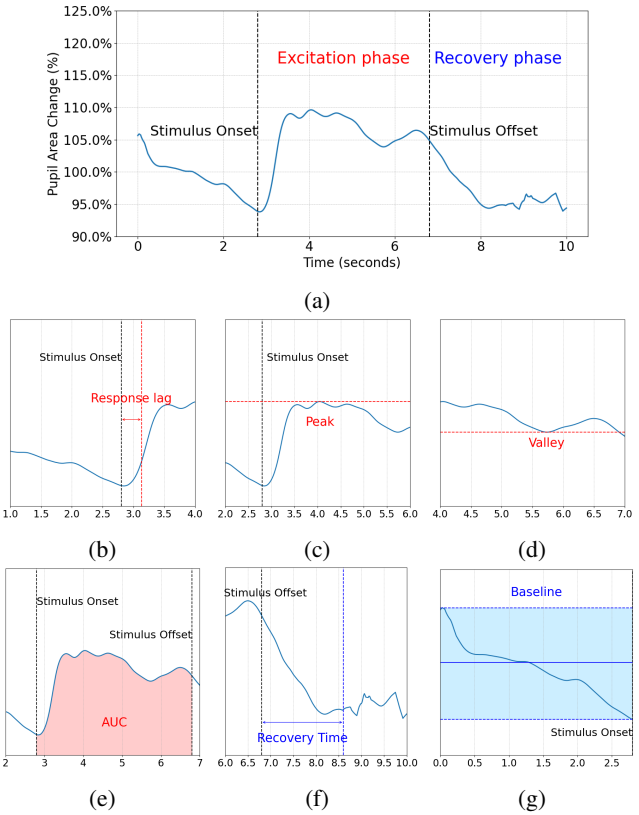


Fig. 4: (a) Illustration of excitation and recovery phase. (b) Response lag. (c) Peak magnitudes. (d) Valley magnitudes. (e) AUC (Area under the curve). (f) Recovery time. (g) Baseline.

tabular dataset, which serves as the foundation for our scoring algorithms. This data enables the extraction of key features that form the basis of our objective scoring system.

The pupil response testing system employs a sophisticated, multi-stage data analysis process, designed to accurately capture the dynamics of pupil response. Initially, the system uses the 'Pupil Detectors' library [14] to extract the pupil area from eye images. Median-based filtering establishes a dynamic threshold for enhancing data consistency, followed by the removal of invalid data points caused by blinks. Users can then manually refine the data through an interactive interface. The final dataset is averaged to provide an accurate profile of the pupil's behavior.

The system also incorporates randomized intervals between individual tests, varying from 2 to 4 seconds, to mitigate the anticipatory behavior of the subjects, ensuring that the responses are as natural and unbiased as possible. This precise data processing, combined with randomized testing intervals, guarantees a high level of accuracy and reliability in capturing pupil response dynamics under varying conditions.

Our data processing effectively filters out anomalies such as blinks and misclassifications, ensuring that only reliable and representative measurements are retained. This phase distills essential metrics from the smoothed and averaged dataset, embodying pivotal facets of the pupillary reflex narrative. Figure 4 illustrates these key metrics, highlighting the nuanced dynamics of the pupillary response.

IV. EVALUATION

A. Design and recruitment of subjects

We conducted a cross-sectional, analytical proof-of-concept study with two groups. The first group consisted of nine patients (n=9, 7M/2F, mean age 37.9 years), diagnosed with moderate to severe hyperacusis, who were evaluated at the Audiology and Speech-Language Pathology Clinic, University at Buffalo. The second group included six healthy participants (n=6, 3M/3F, mean age 32.6 years), recruited through university bulletin board flyers. During the experiment, each participant's left eye was monitored using a 60 frames per second (fps) camera, while two auditory stimuli ("chewing" and "engine" sounds) were presented 10 times each. The experiment was conducted in a soundproof room to ensure precise data collection.

B. Statistical analysis

Due to the limited number of Hyperacusis patients we could recruit, the results of the continuous variables were expressed as the mean with a 95% confidence interval, while qualitative variables were reported as absolute frequency and percentage. A total of 310 trials were selected from an initial 450 trials by removing those with unexpected movements from participants. The comparison of continuous variables between the Hyperacusis Participant and Healthy Participant groups was conducted using the independent t-test. All analyses were performed with a significance level set at $p < 0.05$. Continuous variables were normalized using Min-Max scaling before analysis, and summary statistics, along with p-values.

C. Experimental results

PR Measurement	Hyperacusis (n=9)	Healthy (n=6)	p-value
Response Lag (s)	0.078 (0.059-0.097)	0.096 (0.069-0.123)	0.275
Peak Time (s)	0.219 (0.193-0.245)	0.263 (0.225-0.301)	**0.051**
Peak Value	0.331 (0.319-0.342)	0.321 (0.306-0.336)	0.331
Valley Time (s)	0.223 (0.198-0.248)	0.334 (0.291-0.377)	**0.000**
Valley Value	0.403 (0.393-0.413)	0.376 (0.356-0.395)	**0.019**
AUC	0.333 (0.323-0.344)	0.309 (0.291-0.327)	**0.018**
Recovery Time (s)	0.969 (0.955-0.984)	0.993 (0.989-0.996)	**0.010**

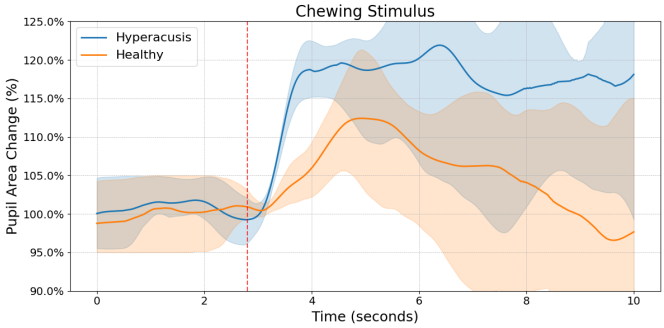
TABLE I: Comparison of Pupil Response Measurements Between Hyperacusis and Healthy Participants

Table I shows the comparison of measurements between hyperacusis and healthy participants for various auditory stimuli. Statistical analysis revealed significant differences in pupil response metrics between the two groups. Hyperacusis patients exhibited shorter response lags and prolonged recovery times, indicating heightened sensitivity to auditory stimuli. Their peak times were consistently faster compared to the control group, suggesting that hyperacusis patients react more quickly to auditory stimuli. Additionally, the higher peak percentages reflect greater pupil dilation, which signifies a stronger physiological response and heightened sensitivity. The valley times, which represent the duration until the pupil returns to baseline size, were longer for patients, indicating prolonged reactivity

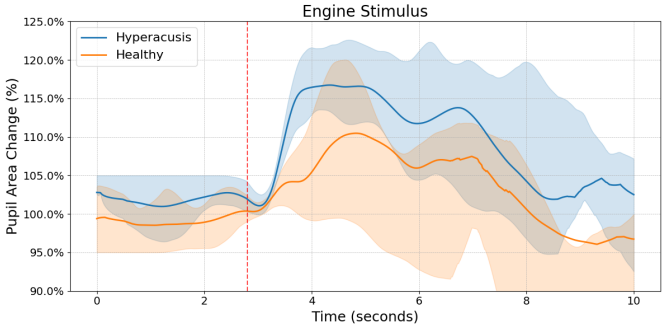
to the stimulus. Furthermore, the area under the curve (AUC) was significantly higher in patients, suggesting a larger and more sustained overall response.

These findings underscore the tool's potential for distinguishing between normal and impaired auditory function, particularly in identifying heightened and prolonged sensitivity in hyperacusis patients. Given the small sample size and individual differences among hyperacusis patients and normal test subjects, the current data is not entirely ideal.

To illustrate the potential differences more clearly, we selected a typical patient and a normal test subject for detailed comparison, as shown in Figure 5. The selected patient exhibited a much shorter response lag and faster peak time, indicating a more immediate and intense reaction. The higher peak and valley percentages, along with a larger AUC, suggest a more pronounced and sustained physiological response in the patient compared to the normal subject. These individual comparisons further highlight the distinct sensitivity patterns in hyperacusis patients.



(a) Pupil Response to Chewing Stimuli in Hyperacusis vs. Healthy.



(b) Pupil Response to Enging Stimuli in Hyperacusis vs. Healthy.

Fig. 5: Pupil Response according to Hyperacusis vs Healthy group and sound type. Mean (central solid line) and IQR (Middle 50% range) are shown for each group.

V. CONCLUSION

Our study introduces a pioneering approach to auditory assessment by utilizing a cost-effective digital tool that analyzes auditory-pupillary responses. The effectiveness of this tool is supported by our experimental findings, which reveal a significant correlation between auditory stimuli and physiological responses. Specifically, hyperacusis patients demonstrate heightened and prolonged sensitivity to various auditory stimuli compared to individuals with normal hearing. However, the current study's sample size is relatively small, and individual differences exist between hyperacusis patients and normal-hearing individuals. These variations highlight the need for further research with larger sample sizes to validate the tool's effectiveness comprehensively.

Future iterations of the system will enhance feature extraction and Pupil extraction precision. By optimizing algorithms and standardizing procedures, we anticipate significant improvements in pupil detection accuracy, thereby reducing the need for manual intervention and facilitating more accurate feature analysis. This groundwork lays the foundation for rapid, reliable, and accessible auditory assessments, particularly benefiting individuals with limited access to healthcare.

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