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Industrial warning system with active devices for signal reception and dynamic noise attenuation using artificial intelligence algorithms

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The protection of workers' hearing in industrial environments is essential to ensure their safety and health. This article presents a general architecture and the essential components of a distributed integrated industrial system capable of receiving notifications from machinery and transmitting voice messages in real-time to workers. Utilizing a localization system based on Bluetooth Low Energy (BLE) technology, the system identifies the real-time position of workers. The one-way communication between machines and the notification server relies on an HTTP protocol with POST requests, allowing the sending of customized alerts to specific groups of workers. This improves communication effectiveness, ensuring that every potentially interested worker receives critical information for their safety. The system consists of two key components: a personal protective device (PPE) equipped with adaptive electronic filters supported by artificial intelligence, designed to dynamically filter harmful noises while allowing the transmission of essential alerts, alarms, and voice communications. The second component includes a user localization system and the transmission/reception between machines and worn PPEs, capable of generating safety alerts and operational instructions, thereby enhancing workers' situational awareness and protection. The article explores the system's architecture and highlights its potential benefits in terms of risk reduction in industrial environments, contributing to the creation of a safer work environment. By emphasizing the importance of technology in safeguarding workers' health, this system represents a significant step forward toward a safer and more responsible industry.

Keywords: Smart PPE, occupational safety, IoT for industry device, dynamic noise cancellation, machine learning for voice detection, real-time audio processing.

1. Introduction

Noise-induced hearing loss and increased accident risks are persistent concerns in noisy workplaces. Protecting workers' hearing without compromising their ability to communicate is a critical challenge in industrial safety. This research introduces a cutting-edge system aimed at managing noise and improving safety through intelligent sound filtering and dynamic response mechanisms. The system is structured into two core components: an advanced Personal Protective Equipment (PPE) device and a human-machine interaction module. The hearing PPE integrates Internet of Things (IoT) (Lee et al. 2015) capabilities and Artificial Intelligence (AI) algorithms to offer adaptive hearing protection and continuous safety monitoring. Central to this design are smart headphones with filters powered by Machine Learning (ML), capable of detecting speech, calculating sound pressure levels (SPL), and dynamically adjusting hardware filters. This functionality is complemented by the second system element, which includes smart machinery and indoor localization tools to provide contextual safety support. Conventional electronic hearing PPE devices often rely on static noise reduction methods that would not ensure optimal speech communication among workers and fail to adapt to varying conditions. The system proposed here overcomes these limitations by utilizing advanced technologies such as Voice Activity Detection (VAD) and Active Noise Cancellation (ANC) (Serizel et al. 2010). Enhanced by neural network algorithms, these techniques enable real-time isolation of speech from ambient noise. Indoor positioning through Bluetooth Low Energy (BLE) beacons adds another layer of safety by tracking workers' locations and generating situational alerts. IoT connectivity facilitates seamless Machine-to-Machine (M2M) communication, ensuring timely intervention during hazardous events. The proposed approach builds on gaps identified in existing PPE solutions, which lack dynamic filtering and fail to integrate with modern safety systems. This system aligns with international and national regulations, such as the Machinery Directive 2006/42/EC (European Parliament and Council 2006), which emphasizes risk reduction in equipment, and Directive 2003/10/EC (European Parliament and Council 2003), which sets exposure limits for noise. Italian Decreto Legislativo no. 81/2008 specifies mandatory PPE usage above 85 dB(A), along with periodic health evaluations. Additionally, ISO 4869 (International Organization for Standardization, 1990) and EN 352 (European Committee for Standardization 2002) establish guidelines for noise attenuation and compatibility of safety devices.

2. System Architecture and Conceptual Design

The conceptual layout of the intelligent hearing protection system, designed and developed in this study, is shown in figure 1. It was established based on the filtering logic of the wearable device and the hazard detection and notification system, with the primary requirements being derived from the state-of-the-art review and the integration of existing technologies. The system's major components include the prototype of the smart headphones and the backend infrastructure for data acquisition and management. The overall architecture of the system is organized into two main subsystems (see figure 1).

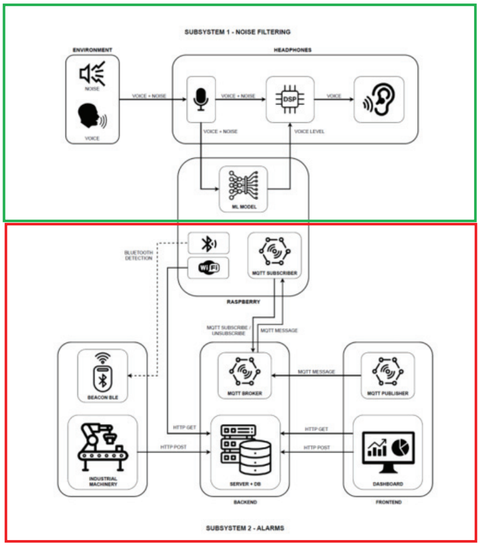


Fig. 1. General system architecture composed by the first subsystem (green box) and second subsystem (red box)

The first subsystem focuses on filtering external noise by detecting human speech in the captured audio and adjusting the filter accordingly. The headphones feature a low-cost electret microphone, which has been previously analyzed for frequency response and directivity pattern, and integrated within the device. This microphone records sound signals composed of speech and/or noise. The recorded audio is processed by a specialized algorithm that analyzes these signals in real time, utilizing a machine learning model, pre-trained in the cloud and executed on a Raspberry Pi®, to identify the presence of speech in the signals (a probability score is provided to distinguish easily understandable speech from noise-immersed speech), as well as calculating the equivalent sound pressure level (SPL). The models incorporate Voice Activity Detection (VAD) techniques (Ramirez et al. 2004), based on Gaussian Mixture Models (GMM) and Deep Neural Networks (DNN) for real-time speech detection in audio. The worker's environment is typically filled with loud, persistent sounds, but it is important that the speech signal of other workers remain audible without being overwhelmed by the machinery noise. A vital role is also played by the Digital Signal Processor (DSP) filter, which, embedded in the headphones, performs real-time adaptive sound filtering using AI-driven algorithms. The DSP detects speech signal data from the real-time audio stream, along with SPL information, and applies noise reduction using Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filters. The Raspberry Pi® serves as the system's central element by executing the Machine Learning VAD algorithm. The second subsystem consists of the backend, which collects and processes data on environmental noise and worker positioning. The backend utilizes a pre-trained Machine Learning model to optimize filter settings in real time for use in personal protective equipment (PPE) to filter sounds. Additionally, the system employs Bluetooth Low Energy (BLE) beacons (Faragher et al. 2015) to track worker locations near machines, providing hazard alerts through synthetic audio messages sent to the headphones. The system is triggered as soon as the worker dons the headphones. When dangerous noise levels are detected, the headphones reduce the noise while allowing significant sounds, such as voices from other workers or alarms, to pass through. The Raspberry Pi® manages the worker's location relative to nearby machinery. Specifically, it continuously scans the surrounding environment to identify all nearby devices that can be detected via Bluetooth. This enables the detection of beacons positioned near machinery. It also handles communication with the backend system, making HTTP requests and dynamically subscribing to MQTT (a messaging protocol for IoT, enabling devices to publish and subscribe to topics for efficient communication in real-time) (Alotaibi et al. 2024) topics associated with the machinery to receive any warnings. The microphone-acquired data is sent to the backend, which processes noise levels, worker location, and machine status in real time. In the event of an emergency, the backend sends notifications via MQTT to workers in proximity to the danger. Each industrial machine is linked to one or more Bluetooth beacons and an MQTT topic, which allows for indoor localization of workers via the Raspberry Pi® connected to the smart headphones. When a worker approaches a machine, the Raspberry Pi® receives a signal packet from a beacon containing an RSSI (signal strength indicator) value. If the RSSI exceeds a specific threshold, the system automatically subscribes the worker to the MQTT topic corresponding to that machine. The smart headphones, having obtained this information during an initialization phase, query the backend server using HTTP requests to confirm the machine-to-topic-to-beacon associations. The backend not only manages the system's database, keeping track of all relevant information, including machine statuses, but also operates the MQTT broker, which is critical for communication between various system components. In case of alarms related to malfunctions or hazardous conditions, the backend receives data from machines via HTTP POST requests (POST is a method used in HTTP to send data to a server, often to create or update resources) (Alam et al. 2014) and relays this information to workers via MQTT topics. Finally, the architecture includes a frontend system accessible by safety managers, who can monitor machine statuses and send hazard alerts or update system data. This dashboard provides a clear, structured visualization of the data and enables active interaction with the backend via HTTP GET requests.

3. System Design and Deployment

3.1. Adaptive Noise Filtering subsystem for Headphones

3.1.1. Low-Cost Microphones

Three low-cost lavalier microphones (Sinclair 2001) were selected for the project, with the potential for integration into the headphones (see figure 2). The selection process, aligned with the project's goals, focused on affordability, a theoretically omnidirectional (Omni in the table 1) polar pattern, and suitability for the audible frequency range. These microphones (see table 1) vary in cost and theoretical performance, which will be validated through testing in both reverberation and anechoic chambers. The microphone demonstrating the best performance in terms of frequency response and directivity will be integrated into the hearing protection device (PPE).

Table 1. Characteristics of Low-Cost Microphones (Mic.).

Mic.	Polar pattern (theoretical)	Audio sensitivity (dB re 1 Volt/Pascal +/- 3 dB)	Frequency Range (Hz)
A	Omni	-32	50 - 20000
B	Omni	-35	20 - 20000
C	Omni	-38	20 - 20000

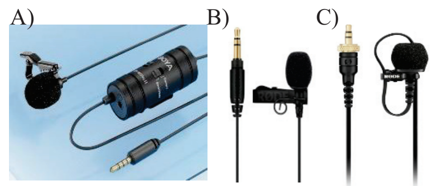


Fig. 2. Selected lavalier microphones

The experimental campaigns carried out in reverberation and anechoic chambers (see figure 3) compared the performance of these low-cost microphones with that of a reference professional Class 1 Sound Level Meter, focusing on their frequency and directional responses. In the reverberation chamber, the microphones were exposed to pure tones ranging from 125 Hz to 8000 Hz, generating equivalent sound pressure levels at the respective frequencies. These levels were then compared to the measurements obtained from the Sound Level Meter. Microphone *A* showed increasing discrepancies at higher frequencies, reaching a maximum error of 8 dB at 8000 Hz. Microphone *B*, on the other hand, had a maximum error of just 1 dB (see table 2) proving to be highly reliable for non-professional applications. Microphone *C* exhibited more significant deviations, particularly beyond 1000 Hz. In the anechoic chamber, the microphones were further tested to assess their directional response. Microphone *B* demonstrated excellent sensitivity, with minimal signal loss (see figure 4), confirming its superior performance in both accuracy and cost-effectiveness, making it the optimal choice for the project's requirements.

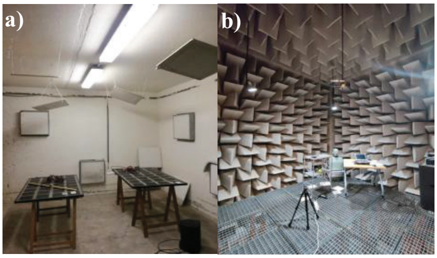


Fig. 3. Experimental campaigns: a) reverberation chamber b) anechoic chamber

Table 2. Comparison of equivalent sound pressure levels (SPL) between sound level meter and microphone *B*: maximum error = 0.9 dB

Frequency (Hz)	Sound Meter Level SPL (dB)	Microphone *B* SPL (dB)
125	94.3	94.6
250	107.6	107.8
500	94.5	95.3
1000	98.4	98.3
2000	105.9	105.4
4000	99.3	100.2
8000	89.6	90.4

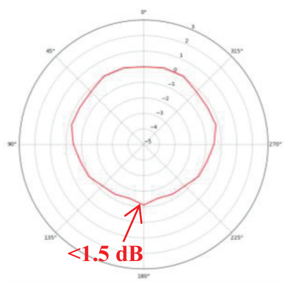


Fig. 4. Polar Pattern of lavalier microphone *B*: good directional response with sensitivity losses under 1.5dB.

3.1.2. Python®-Based Real-Time Processing of Audio Data

A Python®-based software has been developed for noise characterization, leveraging acoustic signal processing libraries like scikit-maad (Ulloa et al. 2021), widely used for environmental acoustic measurements. The system acquires signals from microphones and processes them in real-time, calculating both instantaneous and time-averaged equivalent sound pressure levels and generating spectra in octave or third-octave bands. Initially implemented on a Windows PC, the software was later ported to a Raspberry Pi 5, with comparable analysis times for each 1- second acquisition: 1.3 seconds on the PC versus 3.3 seconds on the Raspberry Pi 5. This discrepancy arises from the stream acquisition time, as computation times for both systems remain under 0.1 seconds per calculation. In addition to scikit-maad, the software incorporates libraries like PyAudio for real-time audio capture, NumPy and SciPy for numerical processing and filtering, and Matplotlib for visualization. A user-friendly graphical interface, developed with Qt Creator, enables intuitive configuration of parameters such as device-specific audio gain, microphone sensitivity, processing bandwidth (octave or third-octave), measurement duration (manual or default), and signal weighting A, C, or Z (Kinsler et al. 1999). Users can select recording modes: *sound level meter* (real-time display and text file recording) or *wave* (saving audio in both .wav and text formats). Before acquisition, microphones and the sound level meter underwent calibration (Myiara 2017) using a professional Class 1 calibrator with 94 dB and 114 dB reference levels at 1000 Hz, determining a dynamic range of 96 dB for 16-bit encoded signals. The software normalizes raw microphone voltage signals to waveform format, similar to recorded .wav files. Using scikit-maad, it calculates sound pressure levels and spectral data in bands. Results are computed every second with exponential averaging using "S" weighting (slow, time weightings = 1 s) (IEC 61672-1 2013), aligning with sound level meter settings for direct comparison. Output includes spectral plots in octave or third-octave bands and time history of the equivalent sound pressure level averaged over the processing duration (see figure 5).

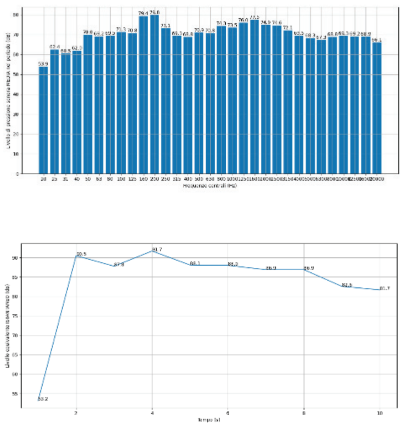


Fig 5. Spectrum in bands averaged over the duration of the individual test and time history, averaged over the measurement time, of the equivalent level

A post-processing program has also been developed for offline analysis of .wav files generated by the real-time algorithm. Using an interface designed with Qt Creator®, the program enables users to select a wave file while automatically detecting its recording parameters.

3.1.3. Smart Headphone Hardware Device

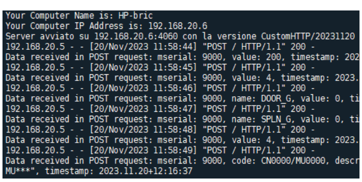
The DSP module selected for the smart headset project is the NEDSP-1901-KBD (see figure 6) from BHI-LTD. This module was chosen for its compact design and real-time audio processing capabilities, including signals from an electret microphone. It supports adjustable noise reduction while maintaining speech intelligibility, offering attenuation levels ranging from 8 dB to 40 dB. These features allow for optimal configuration to significantly enhance voice clarity in various noisy environments. The DSP employs bandpass filtering algorithms that isolate vocal signal components within the 0.2 Hz to 5 Hz range, while attenuating irrelevant frequencies classified as noise. The module is programmable via external microcontrollers; during the testing phase, a simple Arduino board was used, but it can also interface with more complex and miniaturized devices. This programmability enables remote control of functions such as power management and noise filter adjustments. For device testing, a setup was developed using audio recordings simulating industrial environments with typical sounds like chainsaws, pneumatic hammers, and engines. The objective was to evaluate the DSP's performance in noise attenuation while preserving speech intelligibility. The module was integrated with a PCB powered at 12V and connected to audio input and output devices, ensuring efficient signal processing and the application of DSP filters. Additionally, the NEDSP-1901-KBD module features a 7W high-efficiency audio amplifier from Texas Instruments, making it easily adaptable for integration into existing devices. For the final design, miniaturization of the circuit will be essential to fit the module within the ear cups or belt of the PPE. This can be achieved by developing a custom PCB that incorporates all selected components in a smart and compact architecture.

Fig. 6. NEDSP-1901-KBD module

3.2. Human-Machine Interface Subsystem

This subsystem, as previously noted, establishes a connection between industrial machinery, the backend, and the frontend. To replicate this setup, a data transmission architecture was designed to link the machine with the backend server. This architecture integrates a CNC lathe console, the modified Data Collector Manager (DCM) by D.Electron, a Python® HTTP server (running on a PC or Raspberry Pi® 5), and a modem for connectivity (see figure 7). The Python® server script incorporates several libraries: http.server, which facilitates the quick creation of static web servers for development or testing; socketserver, which simplifies server development and customization by handling socket creation, listening, and connection acceptance; datetime, which records the current date and time of the host computer; and socket, which enables manipulation of IP addresses and ports. Communication between the machine and the server is achieved via HTTP POST requests. In this process, the DCM collects, formats, and transmits data (see figure 8) to the server at a specified IP address and port. The transmitted data includes information about the machine's operational status, alarms, maintenance needs, control display status, smart service functionalities, and details of executed programs. As outlined earlier, data is sent in a structured format comprising the machine's serial number, data type, numeric value, value description, and timestamp. During system testing, no data loss was observed, achieving a zero-failure transmission rate. During system testing, no interference was detected, highlighting the stability of the communication channel. The setup time of the system is less than 1 second at the current stage.

Fig. 7. Data transmission layout between machine and server: I) lathe console + DCM, II) HTTP POST server, III) Modem for lathe and server connection



```
Your Computer Name is: HP-bric
Your Computer IP Address is: 192.168.20.6
Server avviato su 192.168.20.6:4060 con la versione CustomHTTP/20231120
192.168.20.5 - - [20/Nov/2023 11:58:44] "POST / HTTP/1.1" 200 -
Data received in POST request: mserial: 9000, value: 200, timestamp: 202
192.168.20.5 - - [20/Nov/2023 11:58:45] "POST / HTTP/1.1" 200 -
Data received in POST request: mserial: 9000, value: 4, timestamp: 2023.
192.168.20.5 - - [20/Nov/2023 11:58:46] "POST / HTTP/1.1" 200 -
Data received in POST request: mserial: 9000, name: DOOR_G, value: 0, ti
192.168.20.5 - - [20/Nov/2023 11:58:47] "POST / HTTP/1.1" 200 -
Data received in POST request: mserial: 9000, name: SPLN_G, value: 0, ti
192.168.20.5 - - [20/Nov/2023 11:58:48] "POST / HTTP/1.1" 200 -
Data received in POST request: mserial: 9000, value: 4, timestamp: 2023.
192.168.20.5 - - [20/Nov/2023 11:58:49] "POST / HTTP/1.1" 200 -
Data received in POST request: mserial: 9000, code: CN0000/MU0000, descr
MU***", timestamp: 2023.11.20+12:16:37
```

Fig. 8. Example of transmitted strings

To replicate a complex industrial environment, the layout has been enhanced using digital twins of typical machine tools. These are realized through virtual clients, developed in Python®/Qt Creator, which emulate the operations of the DCM via POST requests. Each simulated machine is assigned its own client, functioning as a digital twin of the physical machine, capable of simulating operations and complex scenarios in real-time. The digital twin runs on a Raspberry Pi (see figure 9.2). The physical machine included in the layout is a modified CNC lathe, equipped with a PLC for seamless communication with the system supervisor (see figure 9.1). The PLC transmits real-time data regarding machine downtime and emergency conditions, ensuring an uninterrupted flow of information to the backend server. This system enables asynchronous communication between the PLC and the backend, guaranteeing swift and precise responses during emergencies. The architecture is carefully designed to support continuous control and immediate feedback between machines, the digital twin, and the supervisor, optimizing operational management and improving overall system reliability.

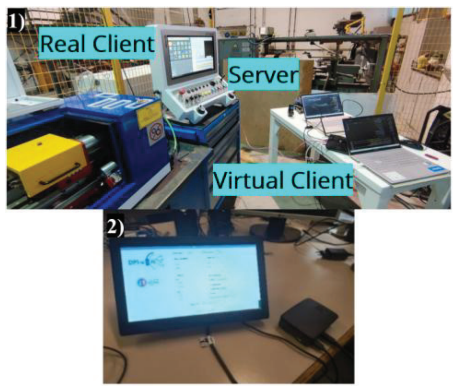


Fig. 9. 1) Data transmission layout; 2) Digital twin of machine on Raspberry Pi

The human-machine feedback system integrates the smart headphones with the work environment, collecting data on ambient noise and monitoring worker positions. This information is processed by a cloud-based Machine Learning model, which analyses the data to send safety alerts or operational instructions, enhancing worker awareness and protection.

4. Conclusion

This work demonstrates an advanced intelligent hearing protection system that leverages IoT and AI for real-time, adaptive noise filtering. By integrating a Digital Signal Processor (DSP) with pre-trained machine learning algorithms for voice detection, the smart PPE attenuates harmful noise by up to 40 dB with a latency below 10 ms, ensuring that essential communications are maintained. The system employs Bluetooth Low Energy (BLE) for indoor localization and uses MQTT for efficient, real-time alert delivery. We are developing a survey and its data indicates that existing hearing protection devices are often underutilized—due to issues like discomfort and communication barriers—or overused, which compromises situational awareness and contributes to high social costs from hearing damage and workplace accidents. Our proposed solution addresses these challenges through a context-aware design that encourages proper use and significantly reduces the associated social costs. Moreover, the system's scalable architecture allows for seamless adaptation across diverse industrial environments without requiring significant hardware modifications. Compliance with regulatory standards such as Directive 2003/10/EC and ISO 4869 further underscores the practical viability of this technology in enhancing workplace safety.

Acknowledgements

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