

Development of a non-invasive ultrasonic sensor network for the measurement of human activities in indoor environment using multi-stage classification process

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ABSTRACT

This study is contextualized in the field of improving indoor comfort measurements, with particular focus in identifying the presence of occupants and discriminating their activities in the environment. Indeed, a non-invasive (and non-wearable) Human Activity Recognition (HAR) system, based on ultrasonic sensors (US) for monitoring activities in office environments, is presented. The methodology has been developed in a controlled environment and involved 10 participants performing predefined office activities. The raw US sensor data has undergone a pre-processing phase, which included calibration to filter out environmental noise and segmentation into 5-s windows. This phase transforms the raw distance data into meaningful displacement measurements that serve as input for classification models. The root mean square temporal marker is extracted and used as input feature in a two-stage classification approach to differentiate between low-intensity and high-intensity activities. Specifically, to increase the accuracy of activity detection, a two-stage classification approach involving both machine learning and deep learning techniques has been developed. In the first stage, the support vector machine classifier distinguishes between static and dynamic office activities with 93.1 % accuracy. In the second stage, a convolutional neural network further classifies specific dynamic office activities, such as writing, typing on a PC, talking on the phone, and standing, with a mean accuracy of 99.3 %. The experimental results confirm the high performance of the proposed HAR system, demonstrating the effectiveness of US sensors for reliable activities recognition. This scalable solution has the potential to enhance user comfort by integrating US-based HAR systems into personalized comfort models and optimizing resource usage in indoor environments.

Section: RESEARCH PAPER

Keywords: human activity recognition; AI-based approach; measurement procedure; ultrasonic sensors; indoor comfort

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1. INTRODUCTION

Quantitatively assessing indoor comfort is essential due to its dual impact on both enhancing the occupants' well-being in living environments and optimizing building energy consumption [1]. Various factors influence indoor comfort, such as environmental conditions, physiological state, and personal factors, including metabolic rate [2]. Studies show that poor environmental parameters such as poor indoor air quality (IAQ) have a negative impact on the occupants' health and productivity and consequently lead to increased investment and operating

costs related to heating, ventilation, and air conditioning (HVAC) systems [3]. Therefore, there is a growing demand for human-centred solutions that also aim at optimizing the building environment management.

In this context, the Personal Comfort Model (PCM) approach is developing as one of the most promising methods to integrate human factors into indoor comfort assessment for consumption control purposes. PCMs predict an individual's thermal comfort based on environmental stimuli (such as thermal, visual, acoustic, and IAQ factors), as well as the individual's physiological state

and unique responses to a given environment [4]. It is well known that thermal comfort perception can vary significantly between individuals, even under the same conditions, due to personal thermal history and physiological factors influenced by different activities [5]. Consequently, integrating Human Activity Recognition (HAR) systems is essential to accurately assess metabolic rate, which is pivotal for the computation of personalized thermal comfort models [6]. The concept of HAR can be applied to different domains, e.g., daily activities, recreational activities, physical activities, intellectual activities, and social activities [7]. Sensing and digital technologies play a crucial role in all these areas, as the non-intrusive nature of sensors enhances the user's acceptance across different populations, and their accuracy directly influences the measurement outcomes [8].

Two main approaches for HAR can be identified in the literature, namely a first approach based on wearable sensors and a second one based on environmental sensors. Wearable sensors [9] are effective for data acquisition, but they are invasive because they require the user to wear them continuously and constantly. An example of these sensors are mobile sensors such as smartphones [10], accelerometers [11], gyroscopes, and proximity sensors. However, despite their practical advantages, wearable sensors present several limitations that can compromise the quality and the reliability of the collected data. First, these devices are inherently invasive, as they require users to wear them continuously and consistently throughout their daily routines. This constant use can lead to discomfort or non-compliance, especially in long-term monitoring scenarios [12]. Moreover, user behavior - such as forgetting to wear the device or wearing it incorrectly - can introduce significant gaps or noise in the data. Another major challenge is the susceptibility of wearable sensors to motion artifacts [13]. External factors such as changes in body posture, sudden movements, or even sensor displacement can distort the signals, leading to inaccurate measurements and potential misinterpretation of the user's activity. For instance, an accelerometer may confuse a brisk walk with a fall if the device moves unexpectedly. Finally, while wearable sensors offer relatively straightforward implementation, their effectiveness heavily depends on consistent user engagement and proper calibration. This makes them less suitable in contexts where passive non-intrusive monitoring is preferred or where user adherence cannot be guaranteed. On the other hand, the second approach focuses on (distributed) sensors installed in the environment, such as cameras, passive infrared (PIR) sensors [14], acoustic sensors [15], ultrasound (US) sensors [16], and thermal sensors [11]. These are seamlessly integrated into the surroundings, making them ideal for developing smart environments, especially when the goal is to minimize intrusion and ensure the natural behaviour of individuals. Indeed, a major advantage of environmental sensors is their non-intrusiveness, as they do not need to be worn or carried by the user. However, it is important to note that non-intrusiveness does not necessarily equate to privacy preservation. In particular, vision-based systems—such as those using cameras—pose significant privacy challenges. While cameras can provide detailed information for HAR [17] and support complex analyses, they also capture identifiable visual data, which can lead to concerns about surveillance and the potential exposure of sensitive personal information.

These concerns are especially critical in public or semi-public spaces, such as government offices, healthcare facilities, and other institutional buildings, where privacy regulations and users'

trust are paramount. In such contexts, the use of cameras may be restricted by legal frameworks (e.g., General Data Protection Regulation GDPR [18]) or may raise ethical objections from occupants and staff, making their deployment problematic or entirely unfeasible.

Furthermore, video-based systems are computationally demanding. Image processing and video analytics require significant processing power and often involve the use of Artificial Intelligence (AI) and machine learning algorithms for activity classification. This adds another layer of complexity, as measurement uncertainties and noise in the visual input can propagate through the analytical pipeline, ultimately affecting the reliability and confidence of the final outputs [19]. Therefore, despite the richness of the data they provide, cameras are often not suitable for long-term activity monitoring in privacy-sensitive environments. In these cases, alternative environmental sensors - such as PIR, thermal, ultrasound or acoustic sensors - offer a more acceptable compromise, as they can detect presence and movement without collecting personally identifiable information.

In this context, the use of US sensors for non-intrusive indoor activity recognition, particularly for activities of daily living such as standing, sitting and falling, is becoming increasingly popular in the research world. US sensors are widely used for distance measurement, allowing precise detection and recognition of these movements [20]. In particular, for this study US were selected due to several practical and ethical advantages compared to other environmental sensing modalities. First, US sensors are relatively low-cost and commercially available, making them suitable for scalable deployment in real-world settings. Their integration into existing infrastructures is straightforward, requiring minimal modifications or calibration. Unlike camera-based or vision systems, US sensors operate independently of ambient lighting conditions, ensuring consistent performance in both daylight and low-light environments. Importantly, US sensing also raises fewer privacy concerns, as it does not involve the capture or processing of personally identifiable visual data. These characteristics make US sensors particularly appealing for preliminary studies aimed at non-intrusive and cost-effective monitoring.

While several studies have successfully achieved high accuracy (around 90 %) in HAR using US sensors, their application is often limited to ceiling installations within apartments [21], [22], primarily focusing on fall detection [23]-[25]. Very few studies explore the use of US sensors for recognizing everyday activities of occupants. To the best of the authors' knowledge, only one study has demonstrated the detection of very small movements using US sensors [26], but the proposed method is limited to for hand gesture recognition.

Therefore, the main contributions of this work are:

- 1) Exploring the capabilities of a desk-mounted, multi-domain system that leverages US sensors for the effective classification of office activities. The proposed system focuses on distinguishing between “static” (e.g., resting) and “dynamic” behaviours (e.g., reading, writing, phone conversation, and standing up) by analysing distance measurements. Distance values detected by US remain stable during passive activities, but exhibit fluctuations during active activities, such as writing, talking on the phone, standing, or moving around.
- 2) Detecting the presence of occupants and classifying activities. In light of the initial assessment described in the first point, a two-step artificial intelligence-based

activity recognition approach was introduced based on US sensors in office environments. Specifically, a methodology based on data preprocessing and key feature extraction prepares the data for the first stage, in which an ML algorithm is used to distinguish between “static” and “dynamic” activities. In the second stage, however, Deep learning (DL) algorithms are used to further refine this classification, allowing “dynamic” activities in the office to be recognized more accurately.

This study was conducted within the framework of the WEPOP project. The WEPOP project adopts an innovative approach that contributes to enhance the personalized well-being measurement considering the human activity influences on comfort. This approach provides useful information also for the thermo-hygrometric control with a view of energy efficiency in living environments. To the best of the authors' knowledge, no existing studies have explored the use of US sensors for HAR within a multidomain sensing device aimed at personalized comfort assessment.

The rest of this paper is organized as follows. Section 2 reviews the related work on HAR. Section 3 presents the methodology used to discriminate different activities. Section 4 presents and analyses the experimental results and gives discussions. Section 5 concludes the manuscript.

2. RELATED WORKS

In the literature, a variety of sensors has been utilized for HAR techniques, each offering distinct advantages depending on the specific application. Traditional sensors such as PIR sensors, microphones, and ultrasonic sensors are commonly employed due to their cost-effectiveness and ease of integration. PIR sensors are often used for detecting motion or presence [27], while microphones capture acoustic signals for activity recognition through sound patterns [15]. Ultrasonic sensors are widely used in proximity-based applications, providing high accuracy in detecting movements and gestures [16]. Additionally, radar sensors, including millimetre-wave radars [28], are becoming increasingly popular for HAR due to their ability to operate in various environmental conditions, including low-light or obscured spaces. Beyond these conventional sensors, recent studies have explored the use of less common or non-conventional sensors for HAR. Thermal infrared sensors [29] have been used for activity recognition in scenarios where thermal signatures of human bodies are distinct, such as in search and rescue operations. Electromagnetic (EM) sensors [30], such as electric field sensors, are being explored for their ability to detect subtle body movements or gestures in a non-invasive manner. Among the sensors described above, ultrasonic sensors were selected for this study due to their unique combination of advantages, being non-invasive, low-cost, and easy to deploy within existing environments. Unlike camera-based or acoustic solutions, they do not raise significant privacy concerns. Furthermore, ultrasonic sensors enable accurate distance measurements and are effective in detecting a wide range of human movements, from gross body motion to finer gestures. These features make them particularly suitable for recognizing everyday activities in a reliable and unobtrusive manner, which aligns with the goals of the present work.

To the best of the authors' knowledge, the integration of the of US sensors in a multidomain sensing device for personalized comfort assessment is an innovative research topic with respect to the state of the art. Similarly, research evaluating the use of US

for discriminating office activities like the ones proposed remains unavailable. Thus, this section discusses the current use of ML and AI approaches applied on signals coming from US sensors for recognizing the human activities.

Ghosh et al. [31] implemented a heterogeneous US sensor grid using 4 HC-SR04 ultrasonic sensors and an LV-MaxSonar-EZO range finder to predict activities such as standing, sitting, and falling. In a controlled environment, this system achieved 81 % to 90 % activity recognition accuracy using decision tree (DT) classification, demonstrating its potential for monitoring human activity in settings like hospitals or homes. They later extended their work to multiple occupants using a Hidden Markov Model (HMM) that combined spatial and temporal features, improving detection accuracy beyond 90 % [21], [32]. Other researchers have explored more complex scenarios. Patel [33] used a sensor fusion approach combining infrared, ultrasonic and passive infrared sensors to monitor activities such as refrigerator and stove use. This system, using Finite State Machine (FSM)-based activity modelling, achieved 96 % accuracy in real-time activity detection. Implementation with ML algorithms, such as logistic regression, Support Vector Machine (SVM) and neural networks, achieved 98.5 % accuracy. Ali et al. [34] introduced a method combining Naive Bayes (NB) and convolutional neural networks (CNNs) to classify normal and abnormal movements using US sensors, demonstrating that hybrid ML algorithms have higher accuracy in activity detection. Similarly, an echo-sound-based activity detector was proposed in [35] to distinguish sedentary office activities with an accuracy in the range of 80.2-85.7 % using cubic support vector machines (CSVMs). DL-based models have also been explored for activity prediction. In [27] US sensors were used to detect activities such as eating, cooking and walking in real time, achieving 86 % accuracy. Another notable work, a deep learning-based framework named EI, was designed to be environment- and subject-independent, achieving better performance compared to traditional methods like random forests (RF) by extracting robust, shared features across different environments [34], [14].

3. MATERIALS AND METHODS

This section describes the methodology for the test protocol employing US used for HAR. Moreover, the strategy for extracting the features related to the different office activities performed by the users and the classification of the office activities are presented.

3.1. Measurement equipment

3.1.1. Ultrasonic sensors

In order to build the HAR system, the US sensor 30201-01 (TDK, Tokyo, Japan) was used. The ICU-30201 is an ultrasonic Time-of-Flight (ToF) transceiver, based on TDK's patented MEMS technology. The sensor integrates a 50 kHz Piezoelectric Micromachined Ultrasonic Transducer (PMUT) with a 2nd generation ultra-low power System on Chip (SoC) in a small, package. The ICU-30201 is ideal to measure distances from 30 cm up to 9 m through pulse-echo measurements, functioning effectively in any lighting conditions, including direct sunlight, and providing millimeter-level accuracy regardless of the target colour or transparency. The sensor customizable Field of View (FoV) can be set up to 180°, allowing simultaneous range measurements of multiple objects. For this work, a 55° FoV was chosen, and a commercial development kit (DK-x0201) from TDK was employed to evaluate the sensor.

To establish the connection and set up the platform for the sensor evaluation, the following hardware components were used:

- Development/host board: DK-x0201;
- Daughter/evaluation board: PN100-06351;
- ICU-30201 module: EV_MOD_ICU-30201-00-0x;
- Flat Flex Cable(s);
- USB Cable.

3.1.2. Environmental sensors

Environmental sensors were utilized to evaluate comfort levels across various domains, including thermal, acoustic, visual, and indoor air quality. In general, the multi-parametric sensors are employed to measure key environmental parameters in indoor settings. The parameters of interest included temperature (T), relative humidity (RH), noise, CO₂ levels, volatile organic compounds (VOC), particulate matter (PM) of various sizes, and brightness. In this study, the low-cost Netatmo environmental sensor (Boulogne-Billancourt, France) was selected for their monitoring. During the test no artificial external audio/visual disturbances and sources were used. The sensors technical specifications and the quantities measured during the tests are reported in Table 1.

3.1.3. Sensors Integration

For the development of a multidomain sensing device, the US sensor and the environmental multidomain sensor were integrated into a single unit. Integration was achieved by placing the US sensor on top of the environmental sensor to face the user and capture the activities performed during the test (Figure 1). Synchronization between the signals from the two sensors was achieved by aligning timestamps and acquisition frequencies.

3.2. Experimental setup

During the test phase, 10 healthy volunteers, including 6 females and 4 males, aged 27.4 ± 2.57 years (mean \pm standard deviation) were involved. Participants were asked to wear their usual clothes to reflect realistic thermal sensations while maintaining the subjective nature of the tests. The tests were conducted over two days - February 27th, 2024, and March 4th, 2024 - in the Room 014 of the Department of Industrial Engineering and Mathematical Sciences (DIISM) at UNIVPM. The room measured $513 \times 296 \times 300$ cm³ and contained two office desks ($180 \times 80 \times 72$ cm³ and $120 \times 80 \times 72$ cm³). Since the tests involved only one participant at a time, only one workstation was used.

To ensure privacy and confidentiality, all data were anonymized and handled in compliance with GDPR regulations. Each volunteer provided informed consent by signing a consent form prior to participation. The study was conducted in accordance with the ethical guidelines outlined in the WMA Declaration of Helsinki and approved by the Ethics Committee of the Università Politecnica delle Marche (UNIVPM), Ancona, Italy. Before the tests, the full test protocol was explained to the



Figure 1. Multidomain sensing device. The US sensors is installed on the Netatmo environmental sensor resulting in a single-unit acquisition device.

participants, with an emphasis on comfort and well-being related measurements. Particular emphasis was put on the non-invasive nature of the sensors, absence of biometric or audio-visual recording, and secure handling of anonymized data.

The multidomain sensing device (Figure 1) was positioned on the subject's desk, located 85 cm and 132 cm from the southwest corner of the room. The Netatmo device was equipped with three US sensors, each with a FoV of 55°, arranged to cover the area around the desk.

For this study, data from the US sensor oriented towards the user were selected and analysed, as it was the only sensor capturing relevant information for distinguishing among different activities. The office scenario involved five predefined activities: "resting", "writing on a paper", "typing on a PC", "phone conversation", and "standing up", as shown in Figure 2.

Prior to each session, an initial setup phase was conducted, during which the participant was instructed to sit for 10 s, followed by standing for additional 10 s. After the setup phase, the actual test began. The sequence of activities was repeated three times, with the entire test lasting approximately 25 minutes. The activity sequence included the following:

- Relaxing, sitting on a chair.
- Writing on paper, using the same form for all the participants, designed during the test protocol development.
- Typing on a virtual worksheet provided during the session.
- Simulating a phone conversation by reading sentences aloud.
- Standing up.



Figure 2. Human activities used to evaluate the performance of the methodology proposed. (a) Resting; (b) Writing on a paper; (c) Typing on a PC; (d) Phone conversation; (e) Standing up.

Table 1: Technical specifications of the Netatmo sensor.

Sensor	Measured quantity	Measurement range	Precision
Netatmo	T	0-50 °C	±0.3 K
	RH	0-100 %	±3 % RH
	CO ₂	0-5000 ppm	
	Noise Level	35-120 m	

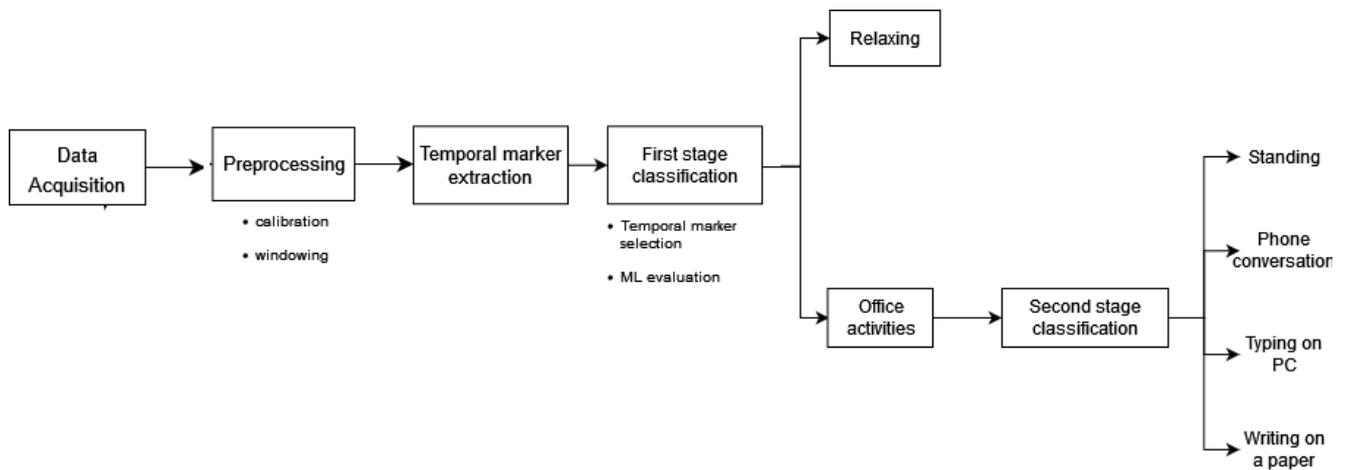


Figure 3. Methodology defined for the HAR classification.

The sequence of activities was displayed to the participants via a webpage on a PC located on the desk. Each session began and ended with a 30-s rest period in a sitting position, and a 30-s rest interval was also included between two consecutive activities for the displacement signal calibration.

3.3. System Architecture

This section outlines the proposed methodology for HAR, which utilizes a multi-stage process to accurately classify activities through AI techniques. The overall methodology, depicted in the block diagram reported in Figure 3, begins with the data acquisition phase, where raw sensor data are collected. This is followed by a preprocessing step, which includes calibration and windowing to extract relevant information. In the next stage, temporal markers are derived from the pre-processed data, which serve as the main features for the classification process. Based on these temporal markers, in the first stage of classification an ML algorithm to distinguish between “resting” (static) and “office” (dynamic) activities is used. After that, the second stage employs DL methods to more accurately identify specific office activities such as writing on paper, typing on a PC, talking on the phone, and standing. With this sequential approach, statistical analysis is combined with two-stage analysis using advanced DL techniques, improving both the accuracy and the detail of the recognized activities. In the following sections, an in-depth analysis is performed on each stage of the proposed methodology.

3.3.1. Pre-processing phase

A pre-processing phase was performed in order to extract useful information from the US data collected. Specifically, a calibration procedure was implemented to filter out distance measurements associated with static elements such as furniture, walls, and the user’s resting posture. To achieve this, US data were recorded in the absence of any user or operator in the testing room, allowing for the creation of an environmental baseline. This baseline was then subtracted from the acquired signals to isolate user-related movements and improve the accuracy of activity recognition. During the first repetition of the activity sequence, the average distance recorded during the initial 30-s resting phase (prior to the writing activity) was subtracted from the US distance data. For subsequent repetitions, the resting phase following the user’s movement within the room was used for this adjustment. Using this procedure, the distance measure recorded by US sensors are turned into displacement

measurement, letting to generalize the HAR independently from the US-subject distance.

After calibration, the US data were segmented into smaller fragments, referred to as windows. A 5-s non-overlapping sliding window technique was employed, chosen specifically to effectively capture and distinguish rapid activities. The window size was chosen based on preliminary testing to balance responsiveness and activity differentiation for short-duration office tasks. This allows us to preserve the key features of the activities performed, enabling more precise discrimination of fast actions in the dataset.

3.3.2. Temporal Markers Extraction

After segmentation, a temporal marker extraction procedure was performed to calculate the feature vector for each data window. This procedure transforms the raw US data into numerical features, preserving the essential information of the original data and ensuring higher accuracy of the results than the direct application of ML or DL techniques to the raw data [25]. Traditional methodologies use temporal markers to discriminate between “rest” (static) and “office” (dynamic) [36]. However, preliminary investigations revealed that temporal markers alone are insufficient to differentiate static and dynamic activities when ultrasonic data are used. To address this limitation, this study employs the temporal markers as input features for AI and ML algorithms of the two-stage classification approach.

Specifically, in the first stage, these markers were used as features for a ML algorithm to differentiate between static activities and dynamic activities. In the second stage, the markers were employed as features for a CNN to further classify distinct office tasks with greater specificity. In this study, four temporal markers were evaluated, i.e., the Root Mean Square (RMS), the Crest Factor (CF), the Form Factor (FF), the Pick Amplitude (PA). RMS and PA were selected due to their sensitivity to motion amplitude, while CF and FF were included to evaluate signal regularity and shape, though they were eventually found to contribute less to inter-class discrimination [37], [38].

The RMS was calculated by taking the square root of the mean of the squares of the signal n data points (x_i) within each window, as shown in Equation (1):

$$RMS = \sqrt{\frac{1}{n} \sum x_i^2}. \quad (1)$$

The CF, also known as the Peak Factor, was determined as the ratio of the peak value (maximum absolute value) to the RMS value for each window, as shown in Equation (2):

$$CF = \frac{\text{Peak Value}}{\text{RMS Value}} \quad (2)$$

The FF was computed as the ratio of the RMS value to the mean of the absolute values in each window, as shown in Equation (3):

$$FF = \frac{\text{RMS Value}}{\text{Average Value}} \quad (3)$$

The PA was computed as the difference between the maximum and minimum displacement values in the 5-s window, as shown in Equation (4):

$$PA = (\text{Peak Value})_{\max} - (\text{Peak Value})_{\min} \quad (4)$$

The rationale for selecting these four temporal markers is based on their ability to capture distinct features, facilitating the classification of static activities, like relaxing, as opposed to various office-related tasks. Markers were extracted by the 5-second sliding window method so that key features of the displacement signal were retained. The dataset included data from 10 participants, each performing 5 predefined tasks with 3 repetitions per task, for a total of 5400 samples. To define which markers to use as features for the two-stage classification procedure, intra-subject (within-participants) and inter-subject (between-participants) analyses were performed to ensure consistent performance and effective generalization across the entire dataset.

3.3.3. First stage classification: Resting activity

In the first stage of classification, ML algorithms were employed to differentiate between “resting” and “office” activities. Effective training of the ML model required selecting the most relevant features capable of capturing the underlying data patterns. This process, addressed in Section 3.3.2., is used as input for the first stage classification algorithm. The algorithms were implemented in the Python environment, using the data splitting method of 70 % for the training phase and 30 % for the testing phase. Three widely used ML algorithms were tested for the classification task, namely Support Vector Machine (SVM), k-Nearest Neighbors (kNN), and Random Forest (RF). These algorithms were selected based on their prevalence and effectiveness in similar studies in the literature on activity recognition. The performance of the classifiers was evaluated using four standard parameters: accuracy (Equation (5)), precision (Equation (6)), recall (Equation (7)), and F1 score (Equation (8)), defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (6)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (7)$$

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (8)$$

3.3.4. Second stage classification: Office activity

In the second stage of the classification process, activities initially categorized as “office” activities were further analysed to identify specific tasks. This step aimed to refine the classification by distinguishing among individual activities, such as writing on paper, typing on PC, phone conversation, and standing up, enhancing the overall accuracy of the HAR system.

For this classification phase, the CNN model was chosen to accurately differentiate the specific office activities performed during testing. The architecture of the proposed CNN, shown in Figure 4, comprises two convolutional layers followed by pooling, batch normalization, and fully connected layers. The first layer is a one-dimensional convolutional layer with 256 filters and a kernel of 5, which uses the rectified linear unit (ReLU) as the activation function. The convolution operation is performed with a stride of 1, followed by a batch normalization layer to improve the stability of the learning process. A max pooling layer with a pooling size of 2 is applied to sample the feature maps. A dropout layer equal to 0.2 was added after the pooling layer to avoid overfitting. The second convolutional layer consists of 64 filters with a kernel size of 3, which continues the feature extraction process. This layer is followed by an additional pooling layer and dense layers to further refine the extracted features. The final CNN layer uses the SoftMax activation function to generate a probability distribution on the target classes output from the classification. The model was trained for 20 epochs with a batch size of 15 using the Adam optimizer and categorical cross-entropy loss.

For the CNN model, standard evaluation metrics (as defined in Equation (5), Equation (6), Equation (7), Equation (8)) were calculated, i.e., accuracy, precision, recall, and F1 score. Additionally, a confusion matrix was generated to provide a detailed analysis of the classification performance between the different office tasks.

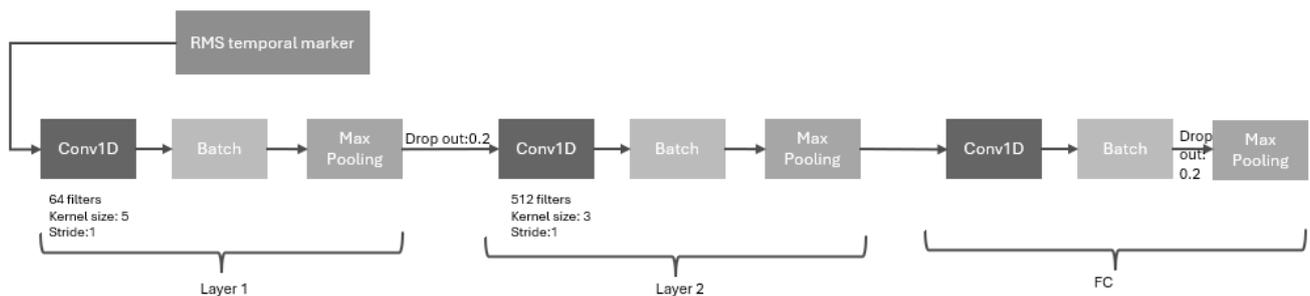


Figure 4. CNN architecture used to classify the HAR.

4. RESULTS

In this section, the authors report the results obtained using the proposed methodology.

4.1. Pre-processing phase result

The HAR methodology proposed in this study starts with two preliminary stages: the pre-processing and the extraction and the evaluation of temporal markers, which are performed before the artificial intelligence classification stages. The pre-processing phase aims to refine the raw data collected by the multi-domain sensing device for the subsequent activity recognition process.

The distance values of the raw US data recorded during testing capture changes in the distance between the sensor and the subject over time, reflecting her/his movements within the monitored space. However, the data also include distances to fixed objects, such as furniture and walls, in addition to those corresponding to the subject's movements. Hence, the raw data extracted from the US sensor must undergo a pre-processing step that involves a first calibration procedure. This step involves filtering out baseline distance measurements related to furniture, walls, and the subject's resting position. By removing these static components, the calibration highlights the actual displacements resulting from the subject's activities. The baseline is recalibrated during rest phases that follow significant movements in the room.

In addition, the data are segmented through a 5-s windowing process on which time markers are calculated. In this way, meaningful time intervals are created that capture periods of activity more accurately (Figure 5). This pre-processing strategy transforms the initially noisy distance data into displacement measurements, which serve as input features for the AI models.

4.2. Temporal Markers Extraction results

To assess the discriminative potential of the temporal markers - RMS, CF, FF, and PA - were analysed across various activities, including "resting", "standing up", "typing on paper", "writing on PC", and "phone conversation". As detailed in Section 3.3.2, both intra-subject and inter-subject variability evaluations were conducted to determine the most suitable markers to be used as input features in the AI classification stages.

Figure 6 (a) and Table 2 presents the average intra-subject RMS values for each activity. The "resting" activity shows lower RMS values than the other office activities ("standing," "paper

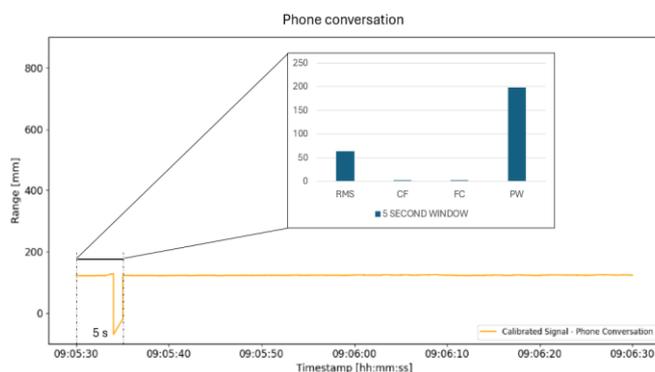
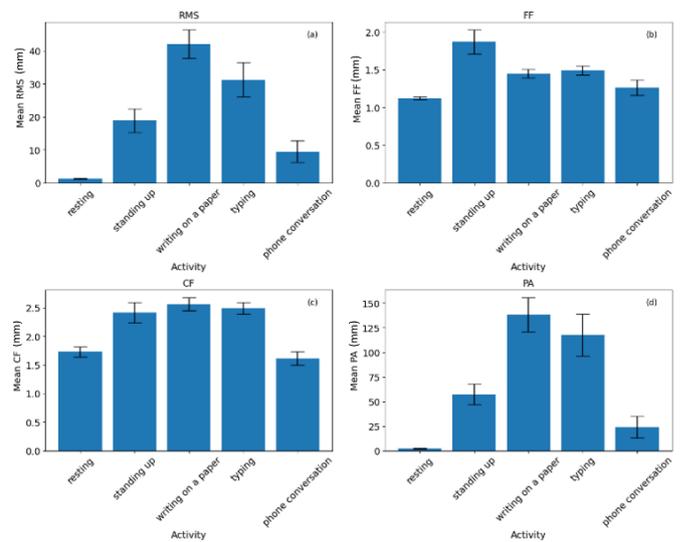


Figure 5. Processed US sensor data after applying the preprocessing approach, which includes calibration and windowing procedures. An example of temporal markers extracted over the selected 5 second windowing is reported.



writing," "PC writing," and "telephone conversation"), which have higher RMS values. In particular, the "writing on paper" activity has the highest RMS values due to the high frequency of dynamic movements, such as gestures and position shifts. This behaviour indicates that RMS is an effective feature in distinguishing between low intensity activities such as rest and higher intensity office activities. In Figure 6 (c), mean CF values show limited variation across activities, suggesting that the frequency component is not distinguishable across activities, whether they are more static or more dynamic. However, a decrease in CF for "telephone conversation" indicates the presence of low-frequency movements during this activity. In contrast, activities such as "typing" and "standing up" have similar HR values as "resting", implying that HR alone is not sufficient to distinguish office activities. Similarly, the average FF values, as shown in Figure 6 (b), show minimal differences across activities, indicating that this feature is consistent for both static and dynamic activities. A slight decrease in FF for "telephone conversation" suggests a greater presence of this low-frequency component in this activity than in the others.

In Figure 6 (d), the average PA values show a clear distinction between "resting" and office activities, indicating that the PA and RMS markers can be used as features for the initial classification phase. From the figures, a distinction in the RMS and PA can be observed among the dynamic activities too. However, when a generalization among all the subject (inter-subject) is performed, the two temporal markers fail to discriminate among the dynamic activities (Figure 7(a) to Figure 7(d) and Table 3).

Overall, RMS showed a superior performance in distinguishing office activities compared to PW both intra-subject and inter-subject, making it the preferred feature for the

Table 2. Intra-subject test results – results are reported as mean \pm standard deviation.

Activity	RMS (mm)	CF (mm)	FF (mm)	PA (mm)
resting	1.24 \pm 0.16	1.73 \pm 0.09	1.12 \pm 0.02	2.30 \pm 0.28
standing up	18.89 \pm 3.57	2.41 \pm 0.18	1.87 \pm 0.16	57.37 \pm 10.42
writing on a paper	42.10 \pm 4.28	2.56 \pm 0.11	1.45 \pm 0.06	138.25 \pm 17.23
typing	31.27 \pm 5.19	2.49 \pm 0.10	1.49 \pm 0.06	117.70 \pm 21.28
phone conversation	9.49 \pm 3.29	1.61 \pm 0.12	1.26 \pm 0.10	23.92 \pm 11.03

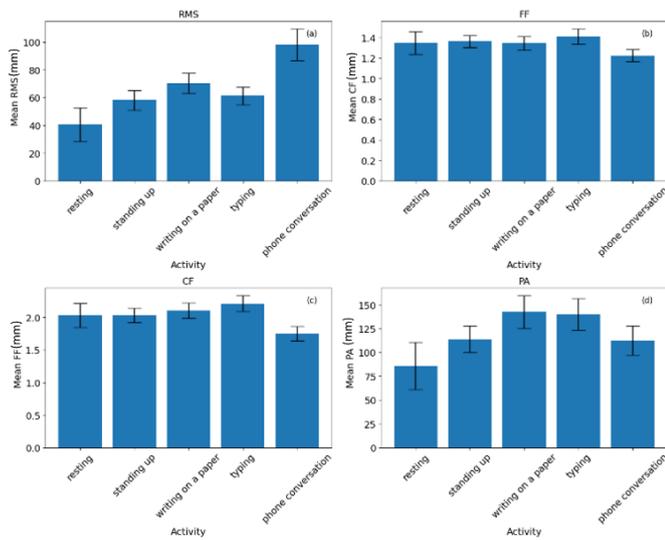


Figure 7. Inter-subject evaluation (Mean and Standard Deviation) of the four temporal markers for the activities selected: a) RMS evaluation; b) FF evaluation; c) CF evaluation; d) PA evaluation.

second-stage classification. Thus, RMS was selected as the primary marker for the detailed recognition of specific office tasks in the subsequent two-step classification procedure.

4.3. First stage classification: Resting activity classification results

As mentioned in Section 3.3.3, for the first stage classification, three ML algorithms were selected. The results of accuracy, precision, recall and F1-score computed using Equation (5) to Equation (8) are reported in Table 4.

The SVM was identified as the best performing algorithm. Therefore, its results were used as input for the second-stage classification, focusing on distinguishing specific "office" activities.

4.4. Second stage classification: Office activity classification results

This section presents the classification results of the CNN designed to distinguish between different office activities. The model performance is evaluated using a confusion matrix, which provides detailed insights into the CNN ability to correctly classify the activities and highlights any misclassifications that occur.

The CNN has an accuracy of 99.3 %, a precision of 99.4 %, a recall of 99.3 %, and an F1-score of 99.3 % in discriminating the office activities. The confusion matrix (Figure 8) presents a detailed overview of the model classification performance across the activities: "standing up", "writing on paper", "writing on PC", "phone conversation", and "resting" activities. The "resting" activity is included because the input to the CNN

Table 3. Inter-subject test results – results are reported as mean ± standard deviation.

Activity	RMS (mm)	CF (mm)	FF (mm)	PA (mm)
resting	40.48 ± 12.27	2.03± 0.18	1.35±0.11	85.86 ± 24.70
standing up	58.06 ± 7.17	2.03 ± 0.11	1.36±0.06	113.86 ± 13.72
writing on a paper	70.50 ± 7.24	2.11 ± 0.12	1.34±0.07	142.35 ± 17.26
typing	61.22 ± 6.46	2.21 ± 0.12	1.41±0.07	139.82 ± 16.80
phone conversation	98.22 ± 11.36	1.75 ± 0.11	1.22±0.06	112.27 ± 15.48

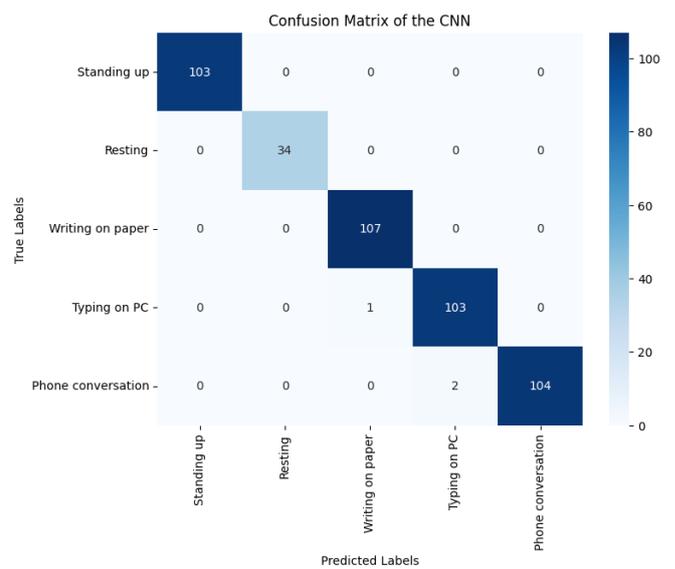


Figure 8. Confusion matrix of the performances of CNN.

comes from the predictions made by the SVM model, which has an accuracy of 93.1 %. This means that the input dataset to the CNN contains false positives due to SVM misclassification errors.

The model accurately classifies most samples for "Standing," "Writing a paper" and "Telephone conversation," with a total of 103, 107 and 104 correct predictions, respectively. There are no significant misclassifications among activities, indicating the model's strong capability to differentiate between the dynamic activities.

5. DISCUSSION

In this work, a methodology for the HAR based on ultrasonic sensors data for a quiet and normal lighting condition office environment is proposed. The methodology consists of steps that allow the identification of features to be used in the two-stage classification approach for detailed activity differentiation in office environments.

The initial calibration and windowing steps ensured that the raw and noisy sensor data were transformed into meaningful displacement measurements by isolating mismatches due to subject movement and filtering out static data such as that related to furniture. Evaluation of temporal markers (RMS, CF, FF and PW) across activities showed the strength of RMS and PA in distinguishing low-intensity activities such as "resting" from more dynamic office activities such as "typing" and "phone conversation." However, the significant differences in RMS values between "rest" and office activities confirmed RMS as the primary classifier for the two-step classification procedure. In contrast, CF and FF showed little variation between activities, indicating limited discriminatory power, especially for activities with similar movement frequencies. Although CF and FF

Table 4. Performance metrics of the ML algorithms used for the first stage classification.

ML algorithm	Accuracy %	Precision %	Recall %	F1-score
kNN	92.6	92.7	99.3	96.1
SVM	93.1	93.1	92.6	100.0
RF	86.3	92.6	92.6	91.9

provide guidance on the content of attendance, they are not sufficient as stand-alone features to distinguish specific activities.

The first classification phase, performed with three machine learning algorithms (kNN, SVM and RF), showed the superior performance of SVM, with an accuracy of 93.1 % and a perfect F1 score (100 %) in separating “rest” and “office” activities. This result made sure to provide a solid basis for the next phase of CNN classification, with only 7.9 % inclusion of “rest” activities in the CNN input (false positives from the SVM phase). This cascade approach is necessary to effectively mitigate the problem of overlapping activity characteristics, especially in scenarios where low-motion office activities could be classified as rest. The second-level classifier, based on a CNN architecture, achieved an overall accuracy of 99.3 % in differentiating among specific office activities. The confusion matrix (Figure 8) provides a detailed summary of the model's performance for five activities: “standing”, “paper writing”, “PC writing”, “telephone conversation” and “resting”. CNN demonstrated the ability to correctly rank the activities 'standing,' 'writing on paper' and 'telephone conversation' (103, 107 and 104 samples, respectively).

These results suggest the effectiveness of the model in handling dynamic activities due to the robust RMS feature extraction and CNN architecture.

Despite the high performance, slight misclassifications were found, particularly between “PC typing” and “Phone conversation”. This could be due to the similarity of the frequency of movements made during the testing phase. For example, two samples of “typing at the PC” were misclassified as “phone conversation,” possibly due to the high similarity of these behaviours of the upper-body movements. However, the low occurrence of these errors (< 1 % of total predictions) indicates that the feature extraction process was effective in minimizing the risks of misclassification error.

6. CONCLUSION

This study introduces a methodology for HAR based on US sensors. The experimental results validate the high performance of the proposed HAR system, demonstrating the effectiveness of US sensors for reliable office activities recognition with an accuracy of 99.3 %. The proposed system is relevant for smart building applications, energy-efficient HVAC control, and privacy-preserving indoor monitoring.

Compared to other sensing technologies, US sensors offer a unique trade-off between accuracy and intrusiveness. For instance, passive infrared (PIR) sensors detect presence based on thermal changes and are mainly effective in identifying transitions between rooms rather than specific activities. Accelerometers can provide fine-grained activity classification when placed on targeted body locations, but they require physical contact and user compliance. Acoustic sensors, while also contactless and capable of detecting a range of activities, may capture speech and other private sounds, raising privacy concerns. Similarly, camera-based systems provide high-resolution monitoring but pose even greater challenges in terms of privacy [39], [40].

In conclusion, compared to existing studies, US sensors emerge as a practical and balanced solution for unobtrusive, activity recognition and they present an innovative approach for integrating HAR systems into PCMs with promising direction for future research by enabling dynamic, user-centered environmental adjustments. Indeed, future works will focus on

expanding the dataset, which is currently limited to a controlled office environment with a predefined set of activities. Increasing the size of the dataset to include a wider range of participants and a greater variety of activities could improve the generalization capabilities of the model, reducing the activities misclassification. In addition, testing the system in environments other than the office setting, such as houses, healthcare facilities, or public spaces, would validate the model under different environmental conditions (e.g., different room arrangements, furniture, and sensors), increasing versatility and applicability in different real-world scenarios.

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