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Internet of Things Assisted Monitoring Using Ultrasound-Based Gesture Recognition Contactless System

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ABSTRACT In the last decade, we have seen an increase in the use of digital technologies in our daily lives, including advanced systems such as mobile applications, smart digital kiosks for intelligent retailing, touch screens for ordering food, or simple implementations such as the ticket machines in the butchers. However, from the perspective of interaction design, those sensing systems suffer from several constraints and limitations such as, low usability and poor hygiene. For example, the elderly or the disabled normally have huge difficulties when interacting with these types of digital systems. Moreover, the recent SARS-CoV-2 pandemic has made us rethink the way we interact with the digital devices. Hence, in this paper, we present a novel solution for digital interaction through a contactless model. This system can provide human gesture recognition and therefore it can be integrated into others to achieve contactless control. We have implemented a prototype based on cost efficient sensors to validate the idea's feasibility. Moreover, a sequence of real world experiments has also been conducted to evaluate its performance. This system is composed with 1) a 3d printed grid of ultrasound sensors to capture the distance information from a human body; 2) software to analyse the data for gesture predictions. This analysis results will be transformed into control commands to interact with the attached system. The experimental results have shown that the proposed system is capable of providing a contactless Human Computer Interaction (HCI), and also has a great opportunity to replace existing touching interaction manner with a remote control scheme.

INDEX TERMS Computer networks, contactless technologies, gesture recognition, ultrasonic sensing, ultrasound sensors, wireless technologies.

I. INTRODUCTION

In the last decade we have witnessed a revolution in the use of digital technologies. This paradigmatic evolution, known as the 3rd digital revolution, marks the beginning of the information age. Never in the history of mankind the access to information and knowledge has been so accessible [1]–[3]. At the heart of this disruptive change is obviously technological evolution, especially digital logic, microprocessors, mobile devices and of course the Internet. In the middle of the past decade, half of the world's population had access to the Internet. This number has risen until today, 2020, to almost 70%.[1] We entered the era of wireless telecommunications where the 5th generation (5G) networks came to interconnect services and unify systems. With the promise of unlimited bandwidth, 5G offers connectivity to users anywhere, anytime. This advent enabled the Internet of Things (IoT) where several automated devices are interconected through the Internet [4]. Several IoT services are emerging on several areas, such as,

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[1]"Worldwide digital population as of April 2020" - Statista. Retrieved 21 May 2020.

e-learning, vehicular networks, smart cities solutions, among others, but especially on remote healthcare [5]–[8]. Today, we easily connect our smartphone via WiFi to a store's payment system, or use a digital kiosks to buy services, such as tickets for the metro or bus. Digital interaction has become a habit of our daily lives, including at home with objects such as the refrigerator or the TV. This digital transformation of the society aims not only to facilitate processes but also to improve the quality of life of its citizens. However, these technologies are not yet ubiquitous to their users and may contain some security problems [9]. One of the obstacles in the use of digital technologies, is its design and its interaction that depend mostly on the human touch [10]. This becomes even more problematic if we consider the use of these platforms by the elderly. The accessibility of digital interfaces and mobile technologies to the elderly population requires special attention when they are built and designed [11], [12]. Unfortunately, in general, they are not adapted for the senior citizens, which in the case of Portugal, represents a large percentage of the population.

Contactless technologies present themselves as non-intrusive and generally present a user-friendly and intuitive interaction. There are several scenarios in which contactless technologies have been successful. From the contactless charger for our smartphone to the door lock access control mechanism of our office, there are already countless examples that have become truly pervasive [13], [14]. These are becoming very important in the smart cities context, especially in the recognition of human behavior or vehicles activity detection [15].

This paper presents an intelligent contactless system as an alternative interaction method for information and communication technology (ICT) systems through intelligent remote gesture recognition. The main objective of this research is to develop a non-intrusive and secure intelligent gesture recognition system for people with disabilities or mobility problems (for example, the elderly). As shown in Figure 1, This prototype includes distance sensors to recognize gestures and trigger smart actions. This system was evaluated through a real testbed pilot where real users operated this system to remotely control a VLC media player.

Although there is room for improvement, results of the performance evaluation attested the feasibility of the system. The proposed system, uses a matrix of ultrasound sensors, therefore allowing to recognize a wider range of gestures. However, in comparison with previous works described in the related work section, that use a small number of sensors and generally recognize less gestures, the performance, especially the accuracy was not significantly affected and presented promising results. Therefore, the main contributions of this article are as follows:

- A detailed review of the state of the art on contactless technology
- The design and construction of a Ultrasound-based Gesture Recognition Contactless System

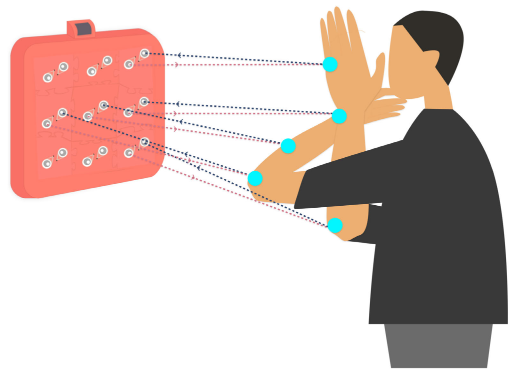

FIGURE 1. Conceptual diagram of the proposed system.

- The Performance evaluation and analysis of the presented system
- Main results discussion, presenting the main contributions to the state of the art

The reminder of this paper is organized as follows: in Section 2 we present some related work on contactless technology and its application in different ways. Section 3 introduces the proposed gesture recognition system and details the key parts of the system in detail, while in Section 4 presents and discusses the experimental results and the performance evaluation. Finally, Section 5 draws conclusions and discusses future work.

II. RELATED WORK

Contactless technology has been growing and used for the past 20 years based on the evolution of smart cards and wireless technologies, such as, Near Field Contact (NFC). Contactless technologies are being applied in several areas, although they are particularly important in the banking and personal authentication industry, attracting the attention of giants such as Google, Apple and Samsung [16]. Among well-known examples, we can highlight, Samsung's "Magnetic Card Emulation" that allows a mobile device to emulate a normal credit card, emulating a magnetic field, as an alternative to NFC.[2] Another example is Google's Host Card Emulation. This Android Operating System solution, stores sensitive information that was previously stored on the smartphone's hardware chip. These technologies are increasingly desirable in a global society that calls for privacy and security. For example, a recent study of more than 7000 travelers showed that 80 percent of hotel guests prefer to use a mobile app to have to check in or out publicly. It is not just a matter of privacy, but also of comfort. 73 percent of the guests wished to have an app that would open their bedroom door and about 50 percent liked having a contactless experience when ordering food either at the bar, restaurant or room service.[3]

Contactless technologies were enhanced by the evolution of wireless technologies such as Radio Frequenciy Idenfier (RFID) or the aforementioned NFC and by the

[2] https://patents.google.com/patent/WO2009082760A2/en
[3] https://www.hotelmanagement.net/tech/survey-travelers-want-contactless-hotel-experiences

well-known Bluetooth and WiFi. In fact, WiFi technologies, available today in any mundane object, allowed its signal to be used for detecting various human activities. With this human sensing, numerous applications were built, ranging from intrusion detection, daily activity recognition, gesture recognition to vital signs monitoring and user identification. This human sensing is a contactless technique that uses a triangulation of the WiFi signal and its reflection with the human body and the walls, floor or ceiling of the room [17]. The recognition of contactless activity has the main advantage of its non-intrusiveness. Although it is a technique widely applied in indoor environments, activity recognition has grown and has gained importance in many applications not only in smart homes, but also in smart cities [18]. In urban settings, activity recognition takes advantage of IoT ecosystems and wearable technologies and includes wireless technologies such as video-based, RF-based and ultrasonic-based [15], [18].

In the healthcare area, the use of contactless technologies has also grown [19], [20] through the adoption of either wireless technologies or IoT ecosystems. In the last decade, the monitoring and collection of vital signs using contactless techniques has received particular attention due to the non-intrusive action and privacy of patients [21], [22]. The use of sensors and cameras in indoor environments for health surveillance and remote monitoring brings clear advantages from a financial and logistical point. For example, the use of video to measure body temperature was widely adopted during the recent SARS-CoV-2 pandemic, however it is a technology that has been in use for some years [23]. One particular healthcare field that wireless contactless technologies have a strong impact is Ambient Assisted Living (AAL) [24], [25]. The AAL aims to provide quality solutions not only, but especially for elderly. These solutions typically use sensors, computers, mobile devices, telehealth systems and rely on wireless and cloud computing technologies [26]. In this sense, several gesture-based contactless solutions were proposed for ill, disable or senior people [27]–[29]. Most of the solutions use cameras for gesture recognition. For instance, [30] a mobile robot is controlled through user gestures to assist disabled and elderly people. The gestures are recognized by a camera in real time and the robot, controlled by wireless technology XBee radio module, receives requests to pick, transport and place objects. The hand gestures defined in this work are the number of fingers. The authors used convex hull algorithm to extract defect and convex points. The number of defect points will determine and recognize the performed gesture. Another gesture-based solution, in this case, to control a powered wheelchair is presented in [31]. Authors used Microsoft's Kinect interface for gesture recognition. The main goal is for disabled people to call the wheelchair through a remote gesture recognition. Microsoft Kinect was discontinued in 2017, however it is still widely used for gesture-based contactless solutions. This system used two cameras, one Red Green Blue (RGB) color model and the other Infrared light (IR) and microphones [32]. In [33] the authors used *Kinect v1* cameras to segment a human hand, capturing just the joins 7 and 8 containing cropping the image to 120×120 px, converting and producing a 2D grid projection of the hand in a grey scale image, and obtaining the outline of the hand, without delving into the subject, would be compared with the 5 trained shapes that the study intended to approach.

Another interesting approach to human gesture recognition is optical sensing and ultrasonic sensing by means of distance sensors. Optical sensing solution are broadly used on hand-gesture solutions [34]. These solutions rely on distance estimation of the target objects. However optical sensors and cameras have considerable power limitations and privacy issues. One potential technology to overcome these constraints is ultrasound imaging. Ultrasound sensors have a low cost and a third of power consumption that optical sensors. Hence, in the last years, several proposals have introduced the use of ultrasound sensors for hand gesture recognition [35]–[38]. For instance, [38] the authors used a single piezoelectric transducer emitting pulses and 8 microphones in the periphery forming a grid, with the purpose of receiving the echo, and thus to create an ultrasonic receiver. All these signals are combined to create images with depth and intensity pixels, in which the hand gestures are determined for the subsequent comparison with 4 trained shapes. Highlighted in this article the idea of using distances to create a map, using the grid structure, can be useful using more accurate sensors.

A. CONSIDERATIONS

The ultrasound-based system presented in this paper gathered contributions from the above-described contactless and gesture recognition solutions. However, it focuses on presenting a solution that detects a greater number of gestures while maintaining performance, without resorting to the use of technologies that require greater processing capacity and energy, such as video cameras.

As above-mentioned, most gesture recognition technologies use cameras or optical sensors, with quite a few limitations. Equally, in general, solutions that use ultrasound or ultrasonic sensors, also usually transform their results into images for analysis of gestures. Our prototype uses a grid of sensors that widens the number of contact points and the number of gestures which are recognized by calculating the distance to the contact points. Thus, our proposal succeeds, compared to those described in the literature, to be a proposal that uses less processing resources and energy, increasing the number of gestures that it can capture.

III. METHODS AND MATERIALS

A. CONCEPTUAL DESIGN/PROPOSED ARCHITECTURE

With the requirement engineering principles in mind we identified multiple key-activities that must be addressed by the prototype, as presented below in high-level format:

- Collect sensors data
- Determine user's distance to the prototype

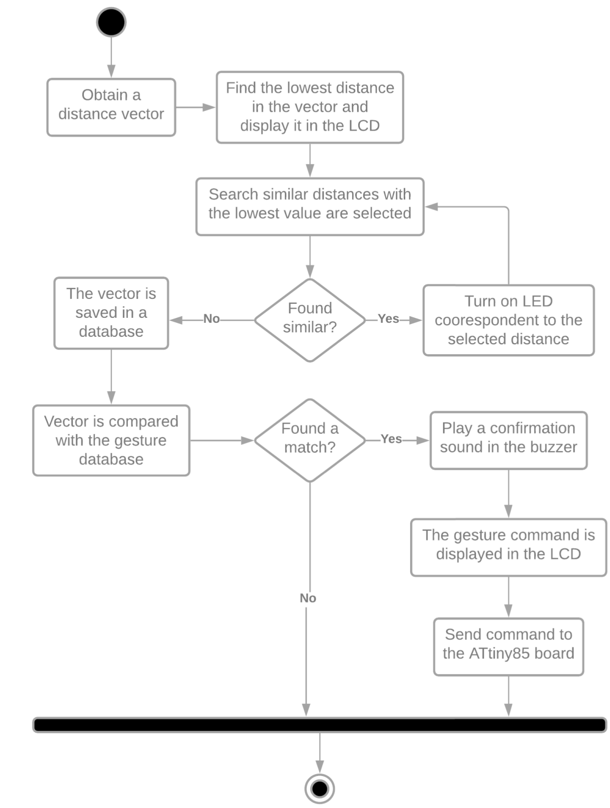

FIGURE 2. **Activity diagram.**

- Feedback on sensors data
- Recognize the gesture
- Feedback on the recognized gesture

On the other hand, these high-level activities were detailed in the activity diagram as depicted in Figure 2 regarding the gesture recognition procedure: (i) obtain a distance vector containing values collected by the sensors grid (i.e. 9 distance values), (ii) the lowest value of the vector is displayed in the LCD, (iii) similar distances with the lowest value are selected (selection criterion based on average arm size), (iv) turn on LEDs correspondents to selected distances (v) the vector is saved in a database, and (vi) is compared with the gesture database, (vii) if found a match then the buzzer is activated and (viii) the command related with the gesture is displayed in the LCD, and (ix) send the command to the ATtiny85 board. The rationale behind the correlation between distance sensors and LEDs lied in the fact that we aimed to provide an instant feedback on user activities. So, when each individual sensor detects the user proximity then the correspondent LED is triggered to notice the user and the research team that sensor was selected into the distance sensors list. In addition, a record is inserted into a *log* file for prospective analysis and debugging.

B. USED TECHNOLOGIES

1) MICROCONTROLLERS

Our experiments were based on the Arduino Mega 2560 microcontroller. The rationale behind the adoption of this circuit board is as follows: (i) it provides a higher input/output capacity (e.g. I/O pins) compared with the Arduino UNO circuit board, (ii) and it also provides a larger flash memory size, namely eight times the offered by the Arduino UNO. Thus, more flash memory means superior capacity to accommodate instructions. However, the Arduino Mega 2560 has a different Universal Serial Bus (USB) controller than the Arduino UNO. Thus, an additional Arduino-compatible circuit board was included into the prototype to solve this limitation which implied the connection of the Arduino UNO to the ATtiny85 as depicted in Figure 3.

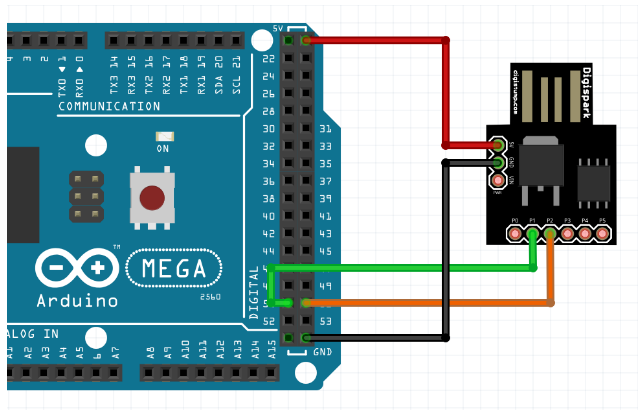

FIGURE 3. **Connection between Mega2560 (left) to ATtiny85 (right).**[4]

2) DISTANCE SENSORS

As the prototype performance relies on the ability of the distance sensor to recognize gestures then a benchmark was implemented aimed at identify the most adequate solution. Thus, three different models were evaluated: (i) an ultrasonic sensor (HC-SR04), (ii) an infra-red sensor (VL53L1X), and (iii) a laser sensor (TOF10120). The benchmark was designed centered in three features that embodied in key system requirements such as:

- Ability to cope with either environment light or outside sunlight, i.e. night and day usage respectively
- Based on signal reflection principles
- Adequate response time

The test bed revealed that both infra-red and laser sensors were capable to detect objects at longer distance but with low accuracy. One reason may rely on the presence of sunlight in the test bed room. On the other hand, based on our experiments when a sensor value ranges higher than 24mm and the Field Of View (FoV) is greater or equal than 25° then were observed erroneous readings in the contiguous sensors. Contrarily, the ultrasound sensor; in spite of its limitation in terms of FoV, provided a more precise value. In fact, was observed that the ultrasound sensor adopted in the prototype is more precise 10mm in spite of a reduced FoV. Figure 4 depicts the work principle of the HC-SR04 ultrasonic sensor.

[4]https://tuxamito.com/wiki/index.php/Digispark

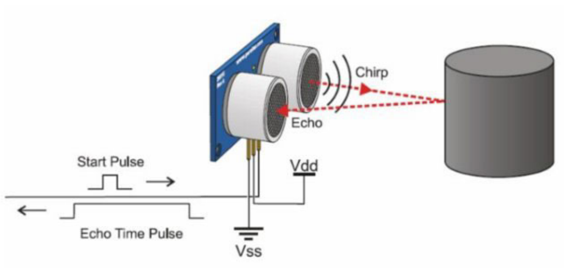

FIGURE 4. Work principle of the HC-SR04 sensor [39].

The distance sensor is the cornerstone of the prototype since it provides crucial information on users' gestures front the device, enabling the system to determine the distance to the user and subsequently to determine its respective gesture.

3) AMBIENT SENSORS AND ACTUATORS

Aiming at to enhance both user experience and system sensing, multiple sensors and actuators were coupled in the prototype, such as: temperature and humidity sensor (a.k.a. DHT sensor), buzzer, and LCD. The DHT11 sensor was adopted on our experiments. However future version of the prototype will include the DHT22 due to its accuracy along with the ability to deal with negative temperatures. The buzzer is useful to provide a real-time audible feedback on the success or fail of the gesture recognition. Thus, a buzzer *piezo* BeStar P3009EB has coupled in the prototype. In addition, this buzzer is also used after a successful system initialization. Finally, a complementary feedback is provided by means of the LCD existing on top of the prototype containing information related with:

- Command (Gesture) to execute
- Temperature in °C
- Icon of last command to executed
- Shortest distance between the user and sensors in cm
- Humidity in %

The Hitachi HD44780 coupled with the LCM1602 module to control the display was used in our experiments. The LCM1602 presents an inter-integrated circuit composed by a set of four wires, 2 related with signal and the remainder for power supply. The gesture iconography is stored in the LCM1602 random-access memory (RAM).

To meet users' expectations and to ease their experience with the prototype, an iconography was created to illustrate all gestures liable to be recognized. Every gesture recognized will display in the LCD the respective icon. The icons collection were created by an online tool,[5] and stored in the LCM1602 random-access memory (RAM). Aiming at to ease the LCD programming the library *LiquidCrystal_I2C.h* [6] was used due to its built-in functions such as: cursor positioning, clear screen, or back light control.

[5]https://github.com/maxpromer/LCD-Character-Creator
[6]https://github.com/johnrickman/LiquidCrystal_I2C

C. POWER SOURCE

The standard USB connection delivers 5V to Mega2560 and allows to draw 500mA in total. Considering that the electrical power provided by the USB microcontroller is not sufficient for the circuit at all, an external DC electrical source; the LIO1473 was added. The use of this power supply is optional, and the batteries can be connected to the DC port of the Arduino Mega2560, having the same max load of 800 mA through the linear power regulator.

Figure 5 depicts the circuit diagram of the prototype including the gesture-capturing, and the correspondent feedback.

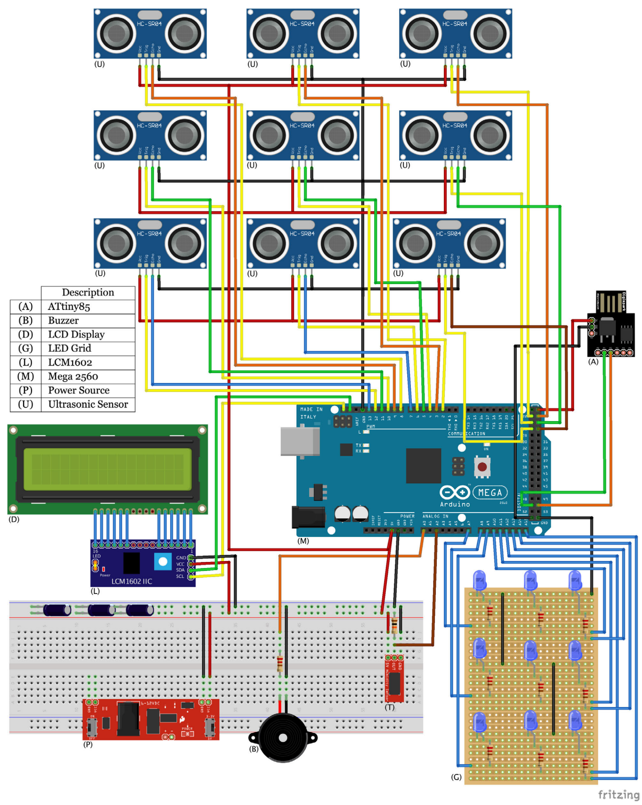

FIGURE 5. Prototype circuit diagram.

D. 3D PRINTED COMPONENTS

The prototype also includes 3D printed components to package the hardware and to protect sensors, actuators and circuit-boards. This structure was designed not only to be robust but also to be adaptable in its shape and size. So, the prototype will be able to accommodate complementary electronic components resulting of extensions and/or enhancements of the prototype. With this principle in mind each individual 3D component was designed to fit all together like Lego bricks. Thus, easily a new 3D component may be included in the structure, and additional room will be available for electronic components. These components were designed in the Autodesk Fusion 360 and the obtained editable file (with the f3d extension) was used to print them in Creality Ender 3X.

In addition, 0.4mm nozzle size was adopted, with an maximum print area of 124 × 175 mm. Moreover, specific 3D components were created to support electronic components and characterized by four plans with dovetail joints and a hole in each corner. Figures 6 and 7 depicts the design evolution of sensors support (from left to right) and its isometric view, respectively.

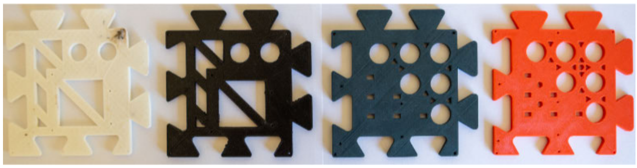

FIGURE 6. Sensors support - design evolution.

FIGURE 7. Sensors support - isometric view.

As depicted in Figure 8, the prototype includes nine distance sensors coupled in a 3 × 3 matrix format which means 3 sensors per row. Since each distance sensor has an associated LED them nine units are also aggregated in the sensor grid. Distance sensors and LEDs are supported by a central axis to ensure stability and robustness on the *apparatus*. Figure 9 provides a complementary perspective on the prototype.

The distance among distance sensors were determined based on the existing literature [40]. Thus, considering that an adult woman has a minimum forearm length of 20.5 cm and an adult man 23.8 cm, the maximum distance from end to end diagonally in the sensor grid is 30 cm,

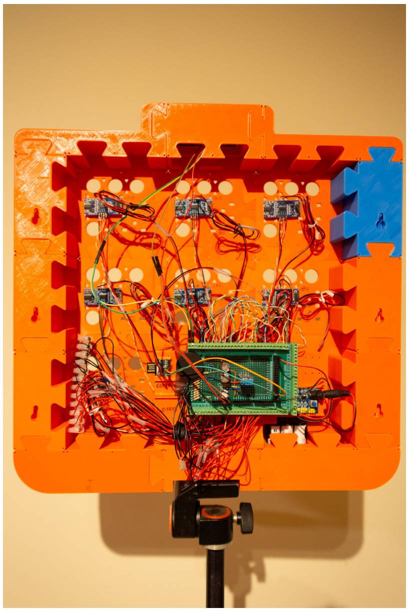

FIGURE 8. Rear view of the prototype.

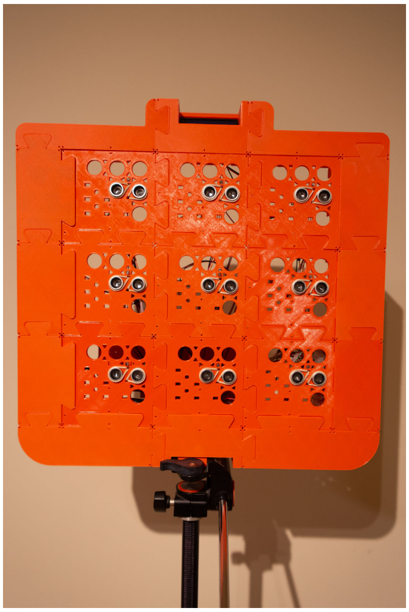

FIGURE 9. The front view of the prototype, where the sensors grid stands out.

E. INITIALIZATION AND DIAGNOSIS

The prototype includes an initialization routine with comprehensive diagnosis on its key features as described in the workflow below:

1) Turn ON the back-light of LCD screen and display the message: "Contactless Gesture Recognition";
2) Play a sound test using inside buzzer speaker;
3) Turn ON all LEDs during 2 seconds;
4) Welcome message is removed from the LCD and environment temperature and humidity value are exhibited;
5) Up to 5 seconds, the boot-loader is completed and a red LED should stop blinking in the ATtiny85;
6) From this moment the USB port is available for connections, since it is detected by the host computer;
7) The lowest distance, in centimeters, between the user and the prototype appears on the LCD;

IV. PERFORMANCE EVALUATION

A. PARTICIPANTS

Twenty-two voluntary participants (10 females and 12 males; aged 22 to 35 years, 2 of them are left-handers), were recruited for the study. All the participants are undergraduate, graduate or master students from a multitude of areas such as

FIGURE 10. Gesture protocol related with Pause, Play, Stop, Next, Previous, Mute, Volume Up, and Volume Down.

TABLE 1. User experience survey questions.

	Question
Q1.	Has the prototype an original design?
Q2.	Has the prototype a suitable size?
Q3.	The prototype is easy to use without review the instructions?
Q4.	Is the gesture recognition time adequate?
Q5.	The visual feedback is enough?
Q6.	Did you consider change your television remote control by a gesture recognition?

computer science, management, marketing, biomedical sciences, bio-engineering, architecture, or music. Each subject was asked to sign a GDPR-compliant informed consent form and completed anonymously a 5-point Likert questionnaire as presented in Table 1. Each scale ranging from 1-strongly disagree to 5 - strongly agree whereas 3 is the neutral answer. All participants reported frequent use of computers and/or smartphones. The participant stood front the prototype at a distance ranging from 2 to 20cm, without any artifact such as jewelry, and wrist watches. The experiment was conducted in a quiet office meeting room. The session started with an explanatory briefing including a training on the eight gestures and the subsequent contactless control of a playlist executed in the VLC media player application on a laptop wireless connected with the prototype. Thus, the participant was asked to accomplish the eight gestures, each one till 12 seconds, for three consecutive times. The gesture protocol is depicted in Figure 10.

B. RESULTS

Table 2, presents the user's feedback in which was observed a completely adherence of participants and thus 22 questionnaires were collected. The design in both originality and size aspects was appreciated by users. In addition, the prototype was considered user-friendly and intuitive. As depicted in Figure 11, the vast majority of participants (82%) strongly agree that the prototype has an original design whereas the remaining 18% agree on it. When inquired about suitability of the prototype size, 73% strongly agree or agree on it.

TABLE 2. Questionnaire results by question.

	Q1	Q2	Q3	Q4	Q5	Q6
Strongly agree	18	5	3	1	16	1
Agree	4	11	10	4	5	10
Neutral	0	4	5	14	1	6
Disagree	0	2	3	2	0	4
Strongly disagree	0	0	1	1	0	1

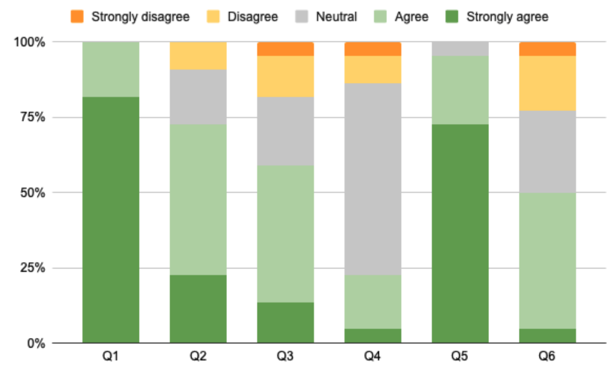

FIGURE 11. Questionnaire results.

On the contrary, 18% are neutral, and 9% considered it with an inappropriate size. Furthermore, 59% of participants highlighted that the prototype is easy to use, in spite of the opposite opinion of 18%. In addition, 64% of participants are neutral related with the gesture recognition time, and 14% considered that it takes too long time. Related with the visual feedback, namely with the adequacy of the LCD 86% of participants strongly agree/agree with it. Finally, 23% participants disagree/strongly disagree with the possibility to adopt the gesture recognition for the remote control of their home television whereas 50% revealed traction for the gesture control adoption. However, several participants pinpointed the system's ability to recognize gestures when they are seat-down watching TV as a critical factor for its acquisition. Otherwise, the user needs to stand up to provide his/her gesture to be recognized by the system which is manifestly uncomfortable and unfeasible.

Our findings also revealed some criticism of participants related with the over-light on both LEDs on the top of sensors and the back-light of the LCD screen, On the other hand, was observed that individuals with larger shoulders experienced difficulties to perform the experiments. These difficulties are due to two factors: (i) the need to approach their elbows perpendicularly with the sensor on either pause or play gestures, and (ii) to differentiate similar symbols displayed in the LCD such as play, and next. In addition, it was observed that female participants easily understood and memorized; as compared with male participants, the multiple gestures recognized by the prototype.

The prototype accuracy was determined; as presented in Table 3 and as depicted in Figure 12, includes a three dimension gesture analysis: recognized, unrecognized, and false positive. Except the Play and the Mute gestures it was

TABLE 3. Gesture recognition accuracy.

	Recognized	Unrecognized	False Positive
Pause	71.21%	21.21%	7.58%
Play	66.67%	30.30%	3.03%
Stop	74.24%	10.61%	15.15%
Next	77.27%	22.73%	0.0%
Previous	78.79%	13.64%	7.58%
Mute	59.09%	37.88%	3.03%
Volume Up	84.85%	9.09%	6.06%
Volume Down	81.82%	16.67%	1.52%

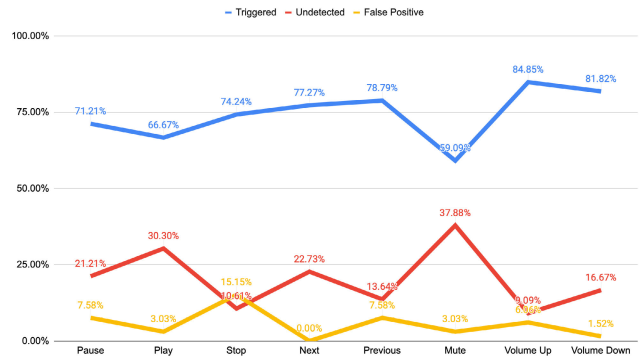

FIGURE 12. Accuracy numerical graphic results.

observed that the remain six-gestures presented a higher accuracy (above 71%). The Play and the Mute gestures revealed an accuracy of 66.67% and 59.09% respectively. These low values are due to the similarity of both gestures, and when unbalanced cross arms is verified then the gesture is prone to be interpreted as a Play. Congruently, our experiments revealed that the Mute and the Play gestures were not recognized respectively on 37.88% and 30.30% of the attempts. In addition, the Pause and Next gestures also revealed a unrecognized rate ranging from 21.21% and 22.73%. Furthermore, the Stop gesture presented the highest false positive rate (15.15%) whereas there were not false positives related with the Next gesture. The average accuracy obtained is 74.24% and the median accuracy is 75.76%.

C. DISCUSSION

This subsection presents a discussion on the potential advantages and constraints of the presented system in this article compared to those described in the related work.

We compared our system with 7 proposals identified in the related work. This comparison was mainly at the level of the equipment and algorithms used, as well as at the level of accuracy obtained. However, it should be noted that several authors used different metrics to calculate accuracy. Therefore, and in order to achieve a comparison as reliable as possible, we used the minimum and maximum values of each work compared to the average accuracy values that resulted from the performance evaluation of our system. The main criterion for choosing the works to compare was those that

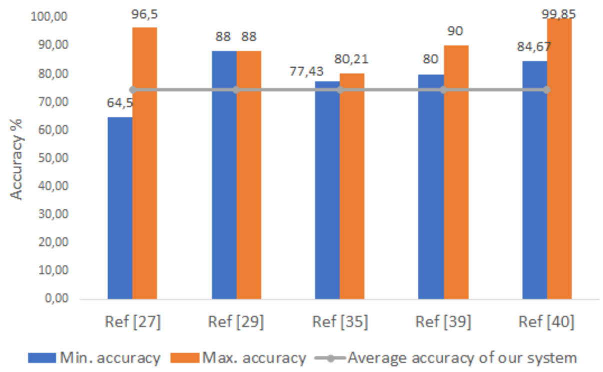

FIGURE 13. Comparison of accuracy performance.

presented performance evaluation of prototypes that focused on gesture recognition.

We found that 4 of the 7 compared works use video/image capture [27], [29], [30], [33] for gesture recognition. Although these systems have high percentages of accuracy in gesture recognition, they also raise several issues and constraints. The images need to be stored and sometimes accessed remotely on web servers (e.g. [27]). This raises several issues and major limitations in terms of power consumption, processing and privacy. Furthermore, these systems usually use software development kits (SDKs) or complex hardware that quickly becomes outdated or even obsolete. For example, Kinect SDK in [33] or the robotic setup in [30].

In terms of accuracy comparison, as depicted in Figure 13, the gesture recognition systems [27] and [29] are based on image capture and analysis and therefore have superior accuracy. Hence, we focus the discussion and comparison of accuracy in systems that use ultrasound-based sensors. We point out that all the identified related works that are being compared with our system have used a controlled test environment for their accuracy evaluation. However, the accuracy results obtained from the performance evaluation above-presented had real participants who simulated a real environment using a VLC media Player. The proposed contactless digital interaction for human gesture recognition performs worse than [36] which achieved an accuracy of 88% by means of combining the ultrasound doppler with the Gaussian Mixture Model (GMM). In addition, [38] designed its gesture recognition model coupling a single piezoelectric transducer and an 8-element microphone array combined with deep leaning methods. The obtained accuracy varied between 64.50% and 96.90%. On the contrary, [37] proposed a 4 channel A-Mode ultrasound device and achieved an overall accuracy of 77.43%. Combining the ultrasound with a surface electromyography the accuracy improved to 80.21%.

Overall, the classification performance of our method aligns with previous work, with considerably less amount of both user re-training and complexity. On the one hand, the gesture classification model relies in a grid of ultrasonic sensors instead of a multitude of sensors with an excessive complexity and/or lower explainability algorithms as observed in other existing solutions in the literature. The proposed method aims to recognize elaborated gestures since it enables left and right arms and hands combined together whereas the traditional approaches based it recognition in either a single hand or a pair arm-hand.

V. CONCLUSION AND FUTURE WORK

In this paper, we have proposed a new idea for system control through contactless human computer interactions which main goal is to provide an effective non-intrusive and secure intelligent gesture recognition system for people with disabilities or mobility problems. To verify the proposed solution, we have developed a prototype with cost efficient sensors. The experimental results have indicated the feasibility of the proposed prototype for gesture recognition. Furthermore, when compared with previous works existing in the literature, the proposed solution, due to the fact that uses a matrix of ultrasound sensors, presents the ability to recognize a larger range of gestures without compromising the overall accuracy of the system.

A questionnaire was also conducted to quantify the quality of user experience afterwards. Through summarising analysis on the feedback, we can conclude that the proposed human gestures recognition system can meet the users' requirements and expectations in terms of design look, usability and responsiveness (system delay). However, more work need to be done in order to improve the Mute and Play gesture recognition accuracy in the *apparatus*.

In the future, we aim to include more testing scenarios to support personalised recognition according to the users own daily living environments. We also aim to improve the hardware set to advance the system's usability, functionalities and robustness. For example, the adopted model for the Arduino Mega requires the inclusion of the ATtiny85 circuit-board which may be suppressed choosing an Arduino provided by a different manufacturer. Furthermore, the brightness of LEDs coupled with sensors should adapt to the environment light. We may choose some higher frequency sensors for more accurate prediction, such as FMCW sensors from Analog Devices or TEXAS Instrument to capture even smaller movements.

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