Brainwave-Controlled System for Smart Home Applications

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***Abstract*—This paper presents an electroencephalogram (EEG)-controlled system for a smart home that is intended to assist disabled and elderly people. The system consists of a NeuroSky MindWave EEG sensor that is paired with an Android application, which is developed to allow the user to control four home appliances. The Android application is paired with an Arduino Uno board using an HC-05 Bluetooth module to control the appliances. The connections between the EEG sensor, the Android application, and the Arduino board are done via Bluetooth, which offers a low power consumption and a portable solution for smart home applications. The system allows the user to individually switch on and off the four appliances using blinking and attention levels. The EEG signal is extracted to analyze the activity of the brain during the experiment. The results agree well with the command, standby, focus, and running modes used during the experiment. The developed system can be easily implemented in smart homes and has high potential to be used in smart automation and wireless biomedical applications.**

***Keywords*—EEG-controlled system, EEG sensor, brain-computer interface, smart home, Android, Arduino**

I. Introduction

According to the World Health Organization, around 15% of the world's population lives with some sort of disability [1]. Such disabilities include brain or spinal cord injuries, multiple sclerosis, brainstem stroke, amyotrophic lateral sclerosis, myasthenia gravis, and cerebral palsy [2]. In most cases, individuals with severe disabilities do not have the ability to interact with their surroundings in order to communicate with other people, move, or control essential tools and appliances. To overcome these issues, various smart devices and appliances have been developed and implemented either individually or integrated together in smart cars, building, and homes. For instance, Y. Moon *et al.* proposed a vanishing point detection model using a harmony search algorithm for autonomous cars [3]. Their proposed method showed a better performance when compared to the commonly used random sample consensus algorithm. The research area of smart homes has witnessed a fast growth in the past few years due to its high positive impact on disabled, elderly, and young healthy people [4, 5]. M. Li and H. Lin proposed a smart lighting algorithm for smart homes by employing power line communication as the network backbone and the wireless sensor network for data sensing [6]. Environmental parameters were obtained to control lighting and other home appliances. In another effort, S. Kumar presented a low-cost smart home system that is controlled using an Android application [7]. The application communicates with a micro-web server to operate several home appliances. Arduino Ethernet was used to eliminate the need for a computer and reduce the cost while utilizing voice activation commands to control the home appliances. A. Hussein *et al.* presented a neural-network-based smart home design that is capable of learning and self-adapting according to disabled people needs [8]. Two neural networks (feedforward and recurrent) were integrated into this system, where the former was used for prediction and learning, while the latter was responsible for security and safety.

However, despite the promising features offered by these works, the ability of disabled people to use such systems is still limited. Several brain-computer interface (BCI) systems have been developed to address the aforementioned issues. Such systems offer a direct neural interface between the brain and other physical devices in such a way that allows the human to communicate and control these devices using different patterns of brain activities [9]. BCI methods can be classified as invasive and noninvasive, where the former requires a surgery to implant electrodes inside or on the cortex, while the latter does not require a surgery [10]. Noninvasive BCI methods include magnetoencephalogram [11], electroencephalogram (EEG) [12], deoxyhemoglobin concentration [13], and blood-oxygen-level-dependent imaging [14]. EEG is the most commonly used method among the noninvasive BCI methods due to its fast response, low cost, simplicity, and ability to implement in portable applications [2]. Thus, several works have been carried out to utilize EEG signals to control various devices and appliances. K. S. Sim *et al.* developed a wheelchair that is controlled using an EEG headset, which is interfaced with a computer and an Arduino board [15]. The users were able to control the movement of the wheelchair with an accuracy of 90%. D. Bright *et al.* demonstrated the control of a prosthetic arm using EEG signals that are processed using MATLAB [16]. The developed arm was able to perform flexion, extension, and pinching with an accuracy of 80%. A. I. N. Alshbatat *et al.* presented an EEG-controlled system for automated home appliances [17]. An EEG headset, a computer, a Wi-Fi module, a quad-band global system for mobile communications/general packet radio service (GSM/GPRS) module, a camera, and a PIC-P40 board were integrated to form the system that controls several appliances in real-time.

Motivated by the promising features of the aforementioned devices, this paper presents an EEG-

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controlled system for home automation, which can be used to assist disabled and elderly people. As a proof of concept, the system allows the user to control four home appliances using an Android application. The application pairs a phone with an EEG headset and an HC-05 Bluetooth module that is connected to an Arduino Uno board. Attention levels and blinking strength values are used to switch on and off the appliances, which offer a suitable solution for disabled and elderly people. The performance of the system and the captured EEG signals are presented to characterized the brain activity of the user and the response of the system during the experiment. The developed system is cost-effective and can be easily implemented in various smart automation and wireless biomedical applications.

II. Design and Working Principle

In this work, a NeuroSky MindWave headset (MW003) (Fig. 1) has been used to measure the EEG signal. The headset is powered by a single AAA battery that allows the headset to have a low overall weight of ~90 g, making it suitable for various remote and portable applications, as well as wireless biomedical applications [18-20]. The dry sensor of the headset extracts 12-bit raw-brainwaves in the range of 3 – 100 Hz with a sampling rate of 512 Hz. The on-board Think Gear chip is used to process and filter the brainwaves from the sensor, and to interface the headset with other devices via Bluetooth. Sensing is achieved by measuring the electrical potential between the electrode placed on the forehead and the reference point (ear clip). NeuroSky EEG algorithm has the ability to perform signal processing to measure the power spectrum density of 7 frequency bands, namely, delta, theta, alpha, low beta, midrange beta, high beta, and gamma. The amplitude of these bands varies according to the internal mental states as well as the external stimulations, as explained in Table I [21]. According to these frequency bands, NeuroSky EEG algorithm can further measure the attention and meditation levels, as well as the blinking strength, where the latter is measured from the spikes in delta and theta bands [22].

An Android application has been developed via Android Studio based on NeuroSky EEG algorithm software development kit (SDK). The Application allows pairing the phone to the headset and to the HC-05 Bluetooth module that is interfaced with an Arduino Uno board. HC-05 was selected as a mean of communicating between the phone and the Arduino Uno board, since HC-05 reduces the power consumption of the phone when compared to using Bluetooth and Wi-Fi to communicate with the headset and the Arduino Uno board, respectively. The Arduino Uno board is then connected to 4 home appliances (a personal computer, a monitor, a Wi-Fi router, and a kettle) using 4 relays (5 V DC JQC-3FF-S-Z) to perform the switching on and off processes, as illustrated in Fig. 2. The Arduino Uno board is programmed with a code that allows receiving the commands from the Android application and translating them into high and low output pins states that control the relays.

Switching on and off these appliances is achieved by detecting the attention levels and double-blinking strength values of the user. The developed Android application requires the user to pair the phone with the HC-05 Bluetooth module and the NeuroSky MindWave headset. Then, the application utilizes NeuroSky EEG algorithm to process the raw EEG signal and detect the signal quality. The application is designed to reject poor-quality signals to prevent inaccurate results. On the other hand, moderate and high-quality signals are utilized to extract the attention levels (0 – 100) and double-blinking strength values (0 – 255). In this case, the application is in a standby mode that waits for the commands of the user. Double blinking with a strength of $\geqslant$ 90 allows the application to be in the command mode. This

TABLE I. EEG frequency bands and related mental states.

Brainwave Type	Frequency range	Mental states and conditions
Delta	0.1 Hz – 3 Hz	Deep, dreamless sleep, non-rapid-eye-movement sleep, unconscious
Theta	4 Hz – 7 Hz	Intuitive, creative, recall, fantasy, imaginary, dream
Alpha	8 Hz – 12 Hz	Relaxed, but not drowsy, calm, conscious
Low beta	12 Hz – 15 Hz	Relaxed yet focused, integrated
Midrange beta	16 Hz – 20 Hz	Thinking, aware of self and surroundings
High Beta	21 Hz – 30 Hz	Alertness, agitation
Gamma	30 Hz – 100 Hz	Cognition, information processing

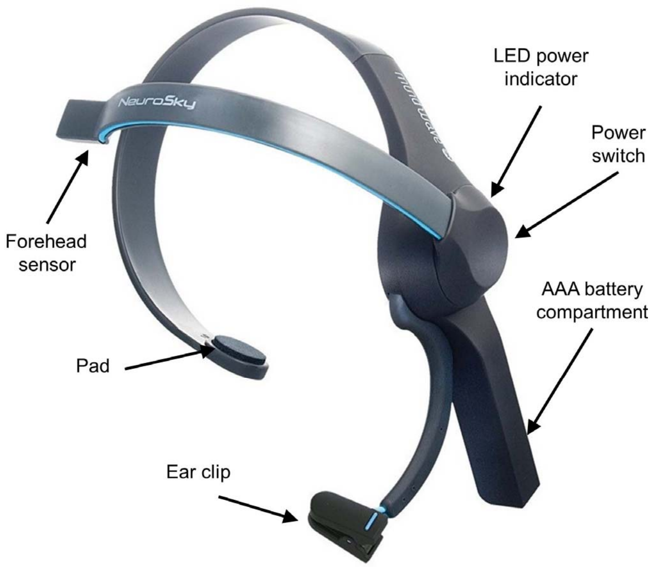

Fig. 1. NeuroSky MindWave headset.

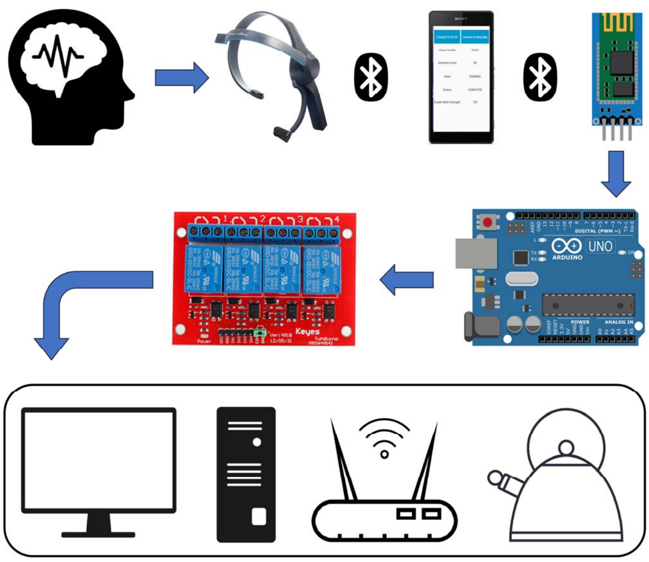

Fig. 2. Block diagram of the working principle.

threshold of double-blinking strength is selected to be above normal blinking levels to prevent any commands caused by unintentional blinking. In command mode, the names of the 4 appliances are displayed sequentially in 2 loops with a time interval of 2 s for each appliance (8 s for each loop). During the total time of the 2 loops (16 s), the user is able to select an appliance by double blinking while the name of that appliance is displayed. Once an appliance is selected, the Android application changes to the focus mode, which requires the user to focus to increase the attention levels to be in the range of 50 – 100 while the name of that appliance is still displayed. These attention levels trigger the running mode, which lasts for 10 s when the attention levels are maintained in the range of 50 – 100. The name of the appliance is fixed in this duration according to the selection made by the double blinks. Then, the desired appliance is switched on/off and the Android application is set back to the standby mode that waits for the command of the user. The aforementioned steps are summarized in Fig. 3, which shows the flowchart of the EEG-based control process.

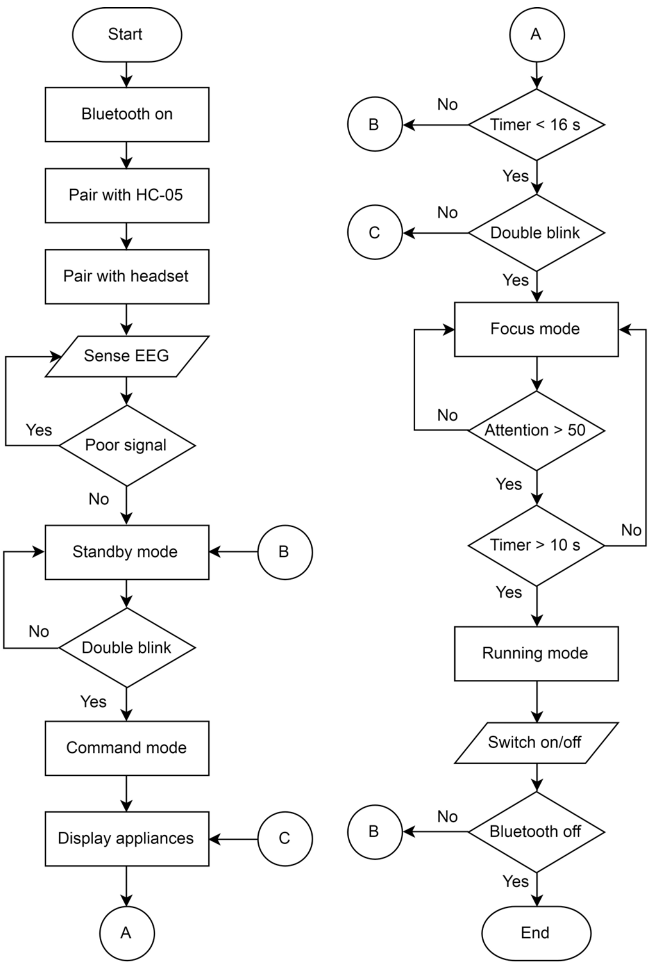

Fig. 3. Flowchart of the EEG-based control process.

III. Results and Discussion

The Android application was built using a build tool version of 26.0.2 with an SDK compiler and a Gradle plugin versions of 23 and 3.0.1, respectively. The application was installed and tested on a Sony Xperia Z3 phone with an Android version of 6.0.1. The Arduino Uno board was powered using a 5 V DC adapter, and the VCC and GND pins were connected to their corresponding pins of the HC-05 Bluetooth module. The TX and RX pins were connected to RXD and TXD pins of the Bluetooth module, respectively, to establish the communication between the Arduino Uno board and the Bluetooth module. Then, the Bluetooth module was set as a slave with a baud rate of 9600 bps using AT commands. TX and RXD pins were disconnected during the rest of the experiment since HC-05 does not receive data from the Arduino board. VCC and GND Arduino pins were also connected to their corresponding pins of the 4 relays. In addition, digital Arduino pins D9 – D12 were set to output pins and connected to the IN pins, which control the opening and closing states of the relays. The live line of an AC 240 V source was connected to the normally open (NO) pins of the relays. The neutral line was connected to one terminal of each appliance, while the COM relay pin was connected to the other terminal. Fig. 4 shows a diagram of the electrical circuit of the system. Initially, D9 – D12 pins were set to be in low states, which keep the relays in normally open states and the connected appliances in off states. Then, each pin is

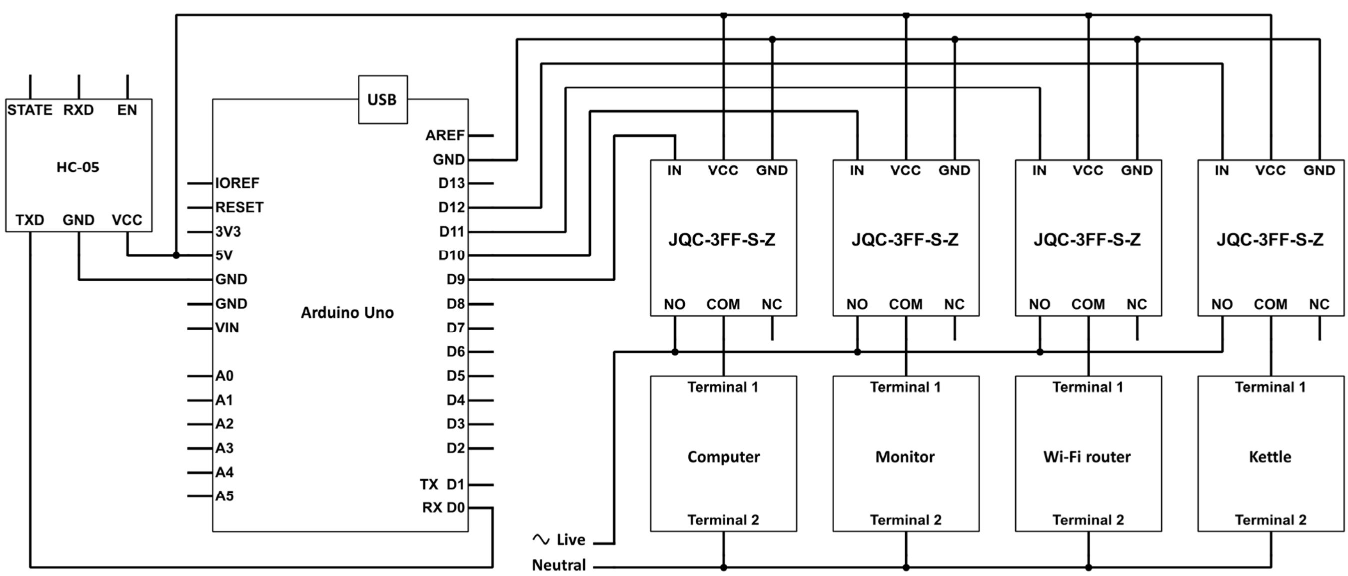

Fig. 4. Diagram of the electrical circuit of the system.

set in a low or a high state according to the commands received from the Android application. A high-state pin causes triggering the input of the corresponding relay, which closes the circuit and turns on the connected appliance. During the experiment, the phone was paired with the HC-05 Bluetooth module and the NeuroSky MindWave headset, while all of the electrical appliances were initially turned off. The user successfully turned on the 4 appliances and then turned them off again in randomly specified or sequential manners. It is worth mentioning that a short training for few minutes is required for the user to understand the working principle and to adapt to the required steps and tasks that need to be performed.

Fig. 5 shows examples of switching on and off tasks performed by the user with screenshots from the phone while the Android application is running during the experiment. In Fig. 5, the control circuit was connected to the appliances as illustrated in Fig. 4. At the beginning of the experiment (Fig.5 (a)), the user was required to turn on the computer, the monitor, the Wi-Fi router, and lastly, the kettle. The Android application was in the standby mode that waits for the double-blinking command from the user to switch to the command mode. Then, the user was able to turn on the computer and the monitor using a separate trial for each one of them, as presented in Fig. 3. Fig. 5 (b) shows the experimental images and screenshots of the Android application after turning the computer and the monitor on, where the screenshot was captured after turning the monitor on. Double blinks with a strength of 171 and an attention level of 62 (at that moment) caused the Android application to switch from the command to the focus and running modes, respectively. Then, the Wi-Fi router and the kettle were switched on using a separate trial for each one of them, as shown in Fig. 5 (c). Double blinking strength and attention level of 105 and 74 (at that moment), respectively, were used to switch on the kettle. The user was then able to switch off the 4 appliances in the same order used to switch them on. The EEG data was extracted during the experiment and then analyzed to characterize the performance and response of the system. In this work, the attention and blinking levels are only the data presented, since the developed system relies on these data only to perform the switching on and off processes. Raw EEG data were processed to extract the attention and blinking levels from the sensed signal, where these levels were calculated using NeuroSky EEG algorithm by considering all the frequency bands presented in Table I.

Fig. 6 shows samples of the attention and blinking levels extracted during the experiment. It should be noted that each double blink is represented by a single peak, since the data processing task is performed each second, while the double blinking action occurs in less that duration. A higher accuracy of blinking detection results was observed when using double blinks rather than a single blink, which explains using double blinking detection in this work. The S periods show successful switching on/off trials by the user, where blinking strength values were $\geqslant 90$ and the attention level values were maintained to be $\geqslant 50$ for 10 s during these periods. The LA period shows a trial where 2 blinking strength values were sufficient to switch the Android application to the command and focus modes, while the attention level values were not maintained to be $\geqslant 50$ for 10 s. Thus, the conditions required to trigger the running mode (Fig. 3) were not fulfilled, which did not result in a switching on/off command. The F period shows a case where the headset failed to detect double blinking levels $\geqslant 90$ despite several trials by the user. Therefore, the Android application was in the standby mode during this period. This can be explained as a result of the limited accuracy offered by the headset and all consumer-grade EEG headsets in general. It is worth mentioning that the low-amplitude oscillations observed in the blinking strength graph are caused by the normal unintentional blinks, muscles movements noise, and the noise caused by inaccurate measurements.

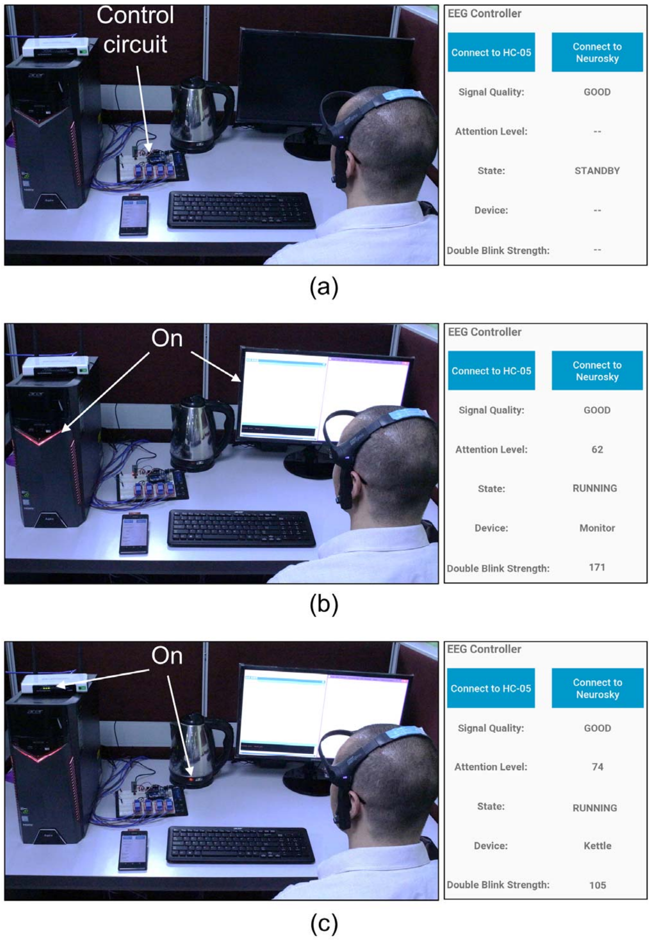

Fig. 5. Samples of the experimental images and screenshots of the Android application: (a) at the beginning of the experiment (all appliances were turned off), (b) after turning on the computer then the monitor, (c) after turning on the Wi-Fi router then the kettle.

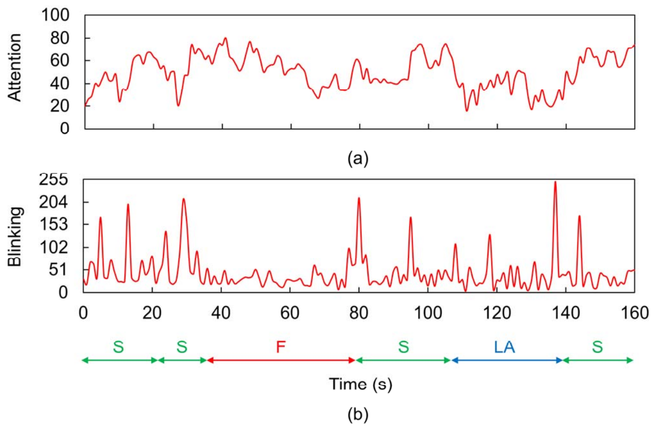

Fig. 6. Sample of the processed EEG data during the experiment showing the (a) attention levels, and (b) blinking strength values.

These results agree well with an in-depth comparison study reported in [23]. The study suggests performing pre-screening of the users by utilizing statistical tests, as well as establishing a proper experimental setup and a motivational environment to overcome the limitation of these headsets. A headset with more sensors and a higher accuracy can possibly improve the results and offer additional tasks that can be performed by the system.

IV. Conclusion

This paper presented an EEG-controlled system for home automation, which is designed to assist disabled and elderly people. The system was developed using a NeuroSky MindWave EEG sensor that was paired with an Android application. As a proof of concept, the Android application was developed to allow the user to control four home appliances. The application was paired with an Arduino Uno board using an HC-05 Bluetooth module to control the desired appliances. The system offers a low power consumption and a portable solution for smart home applications, since the connections between the EEG sensor, the Android application, and the Arduino board were done via Bluetooth. Attention levels $\geqslant 50$ and blinking strength values $\geqslant 90$ were used to switch on and off the appliances, which offer a suitable solution for disabled and elderly people. The performance of the system and the captured EEG signals were analyzed and presented to characterized the brain activity of the user and the response of the system during the experiment. The results agree well with the command, standby, focus, and running modes used during the experiment. The developed system is cost-effective and can be easily implemented in various smart automation and wireless biomedical applications.

Future work will involve using a higher-accuracy headset with more sensors to improve the results and achieve higher flexibility and additional tasks that can be offered by the system. The system can also use Wi-Fi and Internet connection in the future to perform remote tasks in multiple locations. Additionally, this work will also involve integrating other types of sensors, such as ultrasonic sensors for obstacle detection [24] and collision avoidance [25], as well as infrared sensors for shape detection [26] to be implemented in smart cars using human adaptive mechatronics techniques [27]. Future works might also utilize the integration of other wearable sensors, such as electrocardiography sensors [28] to implement the system in wireless passive micropumps [29] and micromixers [30] for implantable drug delivery and other biomedical applications.

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