OpenHealth: Open Source Platform for Wearable Health Monitoring

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***Abstract*—Movement disorders are becoming one of the leading causes of functional disability due to aging populations and extended life expectancy. Wearable health monitoring is emerging as an effective way to augment clinical care for movement disorders. However, wearable devices face a number of adaptation and technical challenges that hinder their widespread adoption. To address these challenges, we introduce *OpenHealth*, an open source platform for wearable health monitoring. *OpenHealth* aims to design a standard set of hardware/software and wearable devices that can enable autonomous collection of clinically relevant data. The *OpenHealth* platform includes a wearable device, standard software interfaces and reference implementations of human activity and gesture recognition applications.**

***Index Terms*—Open source hardware, wearable electronics, health monitoring.**

I. INTRODUCTION

Coupled with an aging population and extended life expectancy, movement disorders are becoming one of the leading causes of functional disability [4]. For example, Parkinson's disease (PD), essential tremor (ET), epilepsy, and stroke affect more than 70 million people worldwide [3]. Diagnosis and treatment of movement disorders currently rely on tests and observations made by specialists in a medical facility, who prescribe medication and therapy based on these observations [10]. However, clinical visits, which are typically weeks apart, capture only a snapshot of the symptoms [6]. This introduces complications in therapy decisions, since symptoms vary over time, and patients' recall accuracy is not reliable [13]. Moreover, access to highly trained specialists can be challenging in many parts of the world.

Wearable sensors and mobile health applications are emerging as attractive solutions to augment clinical treatment and enable telepathic diagnostics [3], [5], [6], [13]. Wearable technology allows for continuous monitoring of user movement in a free-living home environment. This capability helps in capturing the progression of symptoms that change over time. Furthermore, it enables evaluating the prescribed therapy on an individual basis [8], [10], [11]. Similarly, wearable sensors and smartphones have shown promising results in the diagnosis of ET [3] and detecting seizures in epilepsy [13]. Studies have also shown that both patients and health professionals (HPs) value the interactive information available from wearable monitoring. Hence, wearable sensors coupled with telepathic diagnostics can greatly improve health care [8], [13].

Despite the promising results demonstrated so far, widespread adoption of wearable technology is hindered by both technology and adaptation challenges. The International Parkinson and Movement Disorders Society Task Force on Technology identifies the major challenges as non-compatible platforms, clinical relevance of the "big data" acquired by sensors, and wide-spread/long-term deployment of new technologies [5]. According to the task force, open source projects can help in addressing these challenges by providing a common platform, with standardized hardware (HW) and software (SW) tools, driven by burning clinical needs. Several open source solutions for medical devices have been proposed recently. The work in [12] surveys open source devices for infusion pumps, brain-computer interfaces, CT scanners, and physiological monitoring. Among these, the e-Health[1] sensor platform is the most relevant for movement disorders, as it provides sensors for monitoring motion. However, the e-Health sensor platform comes in a large form factor, making it unsuitable for long-term wearable use.

The goal of this work is to discuss the major barriers to widespread deployment of wearable health technology and present the *OpenHealth* framework as a potential solution. *OpenHealth* is an open source HW/SW platform for wearable health monitoring. *Our vision is to bridge the gap between isolated research activities, health professionals, and technology developers by facilitating research using a common platform, standards, and data sets.* Our open source release[2] includes all the HW and SW files of the OpenHealth platform, which includes energy harvesting circuitry, a modular sensor hub, processing hardware, a wireless modem, software drivers, and application-programming interfaces (API). Our initial application area is activity monitoring for movement disorder patients. Future versions of our open source platform will include applications such as fall detection and seizure detection in epilepsy. We also provide reference implementations and data sets for human activity and gesture recognition applications. This feature aims to enable researchers who focus on applications to use *OpenHealth* without dealing with hardware details. All the hardware design files, software repository, and data sets are released under the GNU General Public License.

The rest of this paper is organized as follows. Section II overviews the challenges faced by wearable technologies and our solution strategies. Our vision for the operation of *OpenHealth* and implementation details of our current release are

[1] https://www.cooking-hacks.com/documentation/tutorials/ehealth-biometric-sensor-platform-arduino-raspberry-pi-medical

[2] https://sites.google.com/view/openhealth-wearable-health/home

discussed in Section III and Section IV, respectively. Finally, Section V presents two reference applications, and Section VI summarizes our future directions.

II. Wearable Health: Challenges and Solutions

We classify the barriers to widespread adaptation of wearable health technologies as adaptation and technical challenges, as detailed in Figure 1. The adaptation challenges include social and user-specific barriers that prevent widespread deployment. In contrast, the technical challenges include barriers faced by the designers of the wearable platforms.

Adaptation Challenge 1 - Comfort: A substantial number of patients who participated in previous studies have reported feeling self-conscious when using wearable devices. They anticipate that the wearable device might be a probable cause of stigmatization [9], [13]. The users also expressed feeling embarrassment and awkwardness when wearing the sensor in public. It was stressful to even wear the sensor for some patients [9], [13]. To address this challenge, we propose devices based on flexible hybrid electronics, as illustrated in Figure 4a and detailed in Section IV-A. This approach enables physically flexible or stretchable devices that can blend in with clothes, such as a knee sleeve [1].

Adaptation Challenge 2 - Compliance: Participants in prior studies reported difficulty in using and charging the device regularly. It is difficult for a patient to charge the device, since it may involve taking the device off and wearing it on again [13]. Larger and bulky batteries help in increasing the lifetime of the device, but they also make the device uncomfortable to wear. Studies have also shown that many patients find wearable devices uncomfortable or burdensome and stop using them after some time [3]. Thus, the device should be able to operate autonomously with minimum human intervention. Therefore, *OpenHealth* includes energy harvesting and dynamic energy allocation, which can eliminate battery charging requirements [2]. Furthermore, *OpenHealth* platform operates autonomously to facilitate use without human intervention. More specifically, it automatically turns on, manages the power states and communicates with a host device, such as a smartphone, when it senses motion, as described in Section IV-A. Physically flexible form factor also promotes compliance, as illustrated in Figure 1.

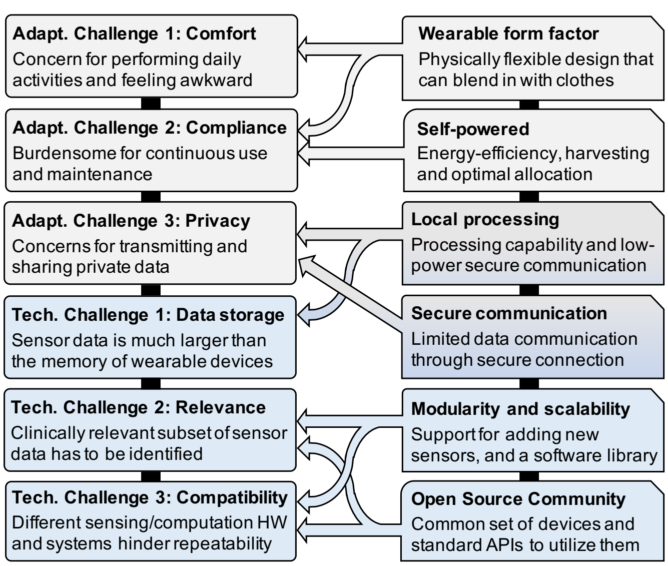


Fig. 1. Challenges of wearable health platforms and proposed strategies

Adaptation Challenge 3 - Privacy: Prior studies have shown that data privacy and security are among the primary concerns about using wearable devices for health monitoring [13]. Raw sensor data could be transferred to the cloud for identification of technology-based objective measures (TOMs). This can cause security pitfalls as the sensor data contains sensitive information about the patient's health. The first solution to this concern is processing the user-specific data locally to the maximum extent possible. For example, motion data from PD patients is processed locally to extract clinically relevant information. Then, *only the processed data* is transmitted through a secure channel *only to the health professional in charge*.

Technical Challenge 1 - Data Storage: Wearable sensors can collect a large amount of data. For instance, a 3-axis accelerometer alone can collect more than 5MB of data in one hour, while the local storage capacity of wearable devices is in the order of few megabytes. Hence, long-term storage of raw data is not sustainable. Since transmitting the raw data would quickly deplete the battery, it is not a viable option either. Therefore, the proposed solution provides local processing capability, as well as a library of signal processing and machine learning algorithms, as detailed in Sections IV-A and IV-B. This strategy also benefits the privacy challenge.

Technical Challenge 2 - Relevance of Sensor Data: Large amounts of sensor data do not necessarily mean that all the data are clinically relevant [5]. In fact, a high volume of data can dilute its direct applicability [10]. Hence, sensors and algorithms should effectively extract relevant information for individualized patient treatment [3], [10]. We address this challenge through two mechanisms. First, the proposed platform features a modular sensor hub that allows adding new sensors for specific use-cases. Furthermore, the proposed platform provides hardware support and built-in functions, such as a variety of filtering and bio-marker generation algorithms. Second, the health professionals are principal members of the open source community. They communicate the clinical needs and TOMs with the developers, as shown in Figure 2 and detailed in Section III.

Technical Challenge 3 - Compatibility: The International Parkinson and Movement Disorders Society Task Force on Technology emphasizes that the majority of technology development efforts operates within its own "islands of expertise", with limited compatibility among the systems [5]. Since devices from distinct manufacturers may give non-compatible results, it is difficult to integrate data provided by different devices. In order to bridge this gap, we propose an open source design methodology where the wearable devices are derived from a common base platform, as illustrated in Figure 2(b) and detailed in Section IV. The compatibility of the proposed solution is improved by using the same underlying hardware, preprocessing software and standard interfaces. This also

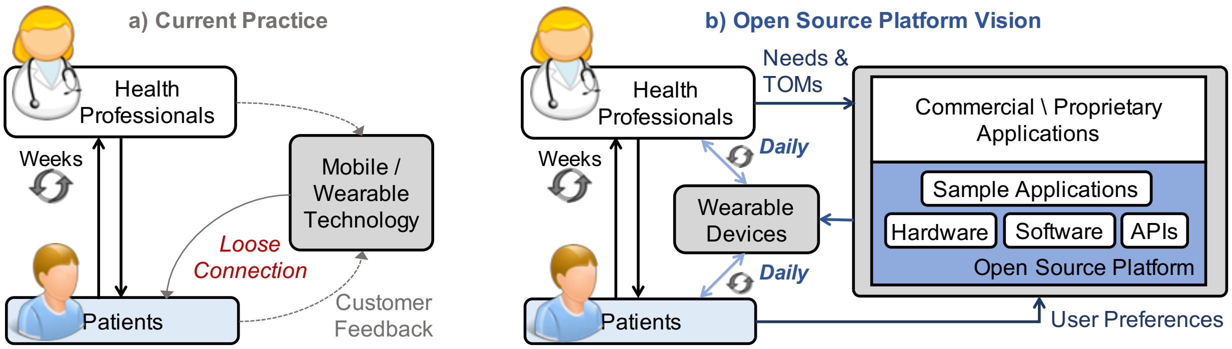


Fig. 2. (a) Current practice of healthcare for movement disorders (b) Envisioned solution with the use of open source wearable platform

facilitates comparing results from different research groups. Finally, open source solutions can constitute the foundation for commercial products, which add new proprietary intellectual property (IP) on top of the commonly used solutions.

Reliability and robustness: In addition to addressing the adaptation and technical challenges, we must ensure that wearable devices are reliable and robust. Reliable and robust design of the device ensures that the device remains operational when subjected to stress during normal use by patients. Common causes of stress for wearable devices include bending, rolling, and folding by patients as a result of their activities [7]. We simulate different bending patterns in finite element simulations to test the device before the manufacturing process.

The device must also be able to continuously sample the sensors, generate the features, and notify a caregiver in case emergencies. This is especially important for life-threatening of emergencies such as seizures in patients with epilepsy. In our proposed solution, we aim at continuous energy-neutral operation by incorporating energy harvesting and a backup battery in the *OpenHealth* platform [2]. Furthermore, we perform on-device processing of the sensor data such that the latency of transferring the sensor data to a host device can be avoided.

III. OpenHealth Vision

Patients with movement disorders primarily interact with health professionals during office visits, which are typically weeks apart. Recently, smartphone apps and fitness trackers have been employed to monitor patients' symptoms during their daily life [6], as depicted in Figure 2a. While this is a useful starting point, these devices are not designed to take into consideration the patient needs. Instead, the patients and health professionals provide feedback after using the device. Hence, they do not address the social and technical challenges, such as comfort, compliance, and clinical relevance, as discussed in Section II. Consequently, the connection between the patients' needs and device capabilities is loose.

OpenHealth aims to provide a comprehensive framework that enables a tighter and systematic interaction between all the stakeholders in wearable health monitoring, as illustrated in Figure 2b. Open source communities can bridge isolated research efforts, health professionals, and HW/SW developers to address the social and technical challenges [5]. In this framework, health professionals provide needs and clinically relevant TOMs to the developers. TOMs are defined as technology-based objective measures provided by device-based clinical tests conducted in a standardized environment to have an objective assessment of specific behavior related to a movement disorder [5]. TOMs can also include the tests self-administered by patients to monitor symptoms in everyday life. TOMs help the health professionals in assessing patient symptoms such that the quality of care can be improved [5]. The second input consists of preferences of the patients, who are the end users of the wearable devices, as shown in Figure 2b. The preferences include materials used in the device, form factor, and battery life. These inputs from HPs and patients ensure that the wearable devices developed meet the requirements of the users from the onset, rather than relying on customer feedback.

The open source hardware and software is developed with the inputs from health professionals and users to address their requirements and needs. The *OpenHealth* platform also includes standard APIs, reference applications, and data sets. These APIs can be used by researchers to develop their own applications to detect and monitor TOMs without mastering the hardware design. An open source platform is important because it enables compatibility and standard comparisons of data. It can also enable the generation of common data sets for movement disorders, analogous to data sets such as the MNIST database[3] for image recognition. This can give a boost to the research in the area of movement disorders. In addition to the base open source platform, third parties can develop their own commercial applications as extensions to the base platform, as illustrated in Figure 2b.

The final step in the OpenHealth architecture is the real-world usage of wearable devices by patients and clinicians. The wearable device supplements the existing office visits, which could be weeks apart. In our *OpenHealth* vision, the wearable device provides daily feedback of TOMs and other relevant parameters to both patients and their HPs. This allows HPs to monitor the symptoms of their patients in real-time, allowing them to make better therapeutic decisions. Similarly, patients can benefit by having access to daily feedback about their symptoms from both HPs and the algorithms on the

[3] http://yann.lecun.com/exdb/mnist/

wearable device. As a result of this daily feedback, large improvements to the quality of life of patients can be made.

IV. OpenHealth Release

The main components of the *OpenHealth* platform are shown in Figure 3. The hardware stack in the base platform consists of most commonly used sensors, a microcontroller unit (MCU), radio and energy harvesting circuitry. Similarly, the base software stack consists of the real-time operating system (RTOS), sensor APIs, communication services and reference applications. In addition to the base platform, the wearable platform can be extended with additional sensors, algorithms, and applications.

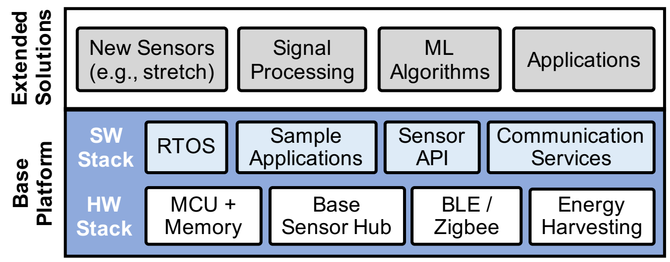


Fig. 3. Overview of the wearable platform

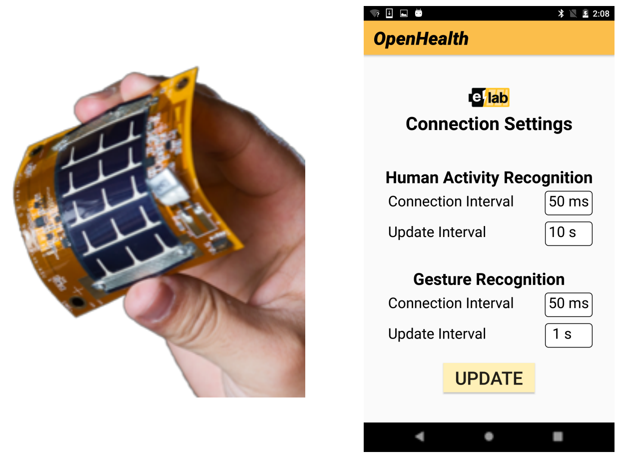
A. The Base Hardware

Processing Unit: Texas Instruments (TI) CC2650 MCU[4] is the main processing unit in our base hardware. It consists of an ARM Cortex-M3 core with an operating frequency of 47 MHz. The MCU includes 20 KB of SRAM and 128 KB of programmable flash. In addition to the main Cortex-M3 core, it also includes a low power sensor controller that can run autonomously from the rest of the system. The sensor controller can be used to monitor sensors while the rest of the system is in a low power sleep state. To ensure autonomous operation, the device is always on, but it waits in low power mode until it detects active motion. When motion is detected, the device wakes up and starts collecting sensor data. Then, the MCU executes the target application, such as human activity or gesture recognition, as detailed in Section V. The outputs are transmitted to a host device, such as a smartphone, without any user intervention after setting the connection settings with the host device, as illustrated in Figure 4b. These settings control how often the wearable device synchronizes with the host. As mentioned before, on-board processing capability allows us to perform the processing of TOMs in real-time, thus eliminating the need to transfer the raw data.

Sensor Unit: The sensor unit in our base wearable platform consists of the Invensense MPU-9250[5] motion sensor and electromyography (EMG) sensors. The MPU consists of a three-axis accelerometer and a three-axis gyroscope. They are used to track the motion of the user wearing the device. Similarly, the EMG sensor is used to record the electrical

[4]http://www.ti.com/product/CC2650

[5]https://www.invensense.com/products/motion-tracking/9-axis/mpu-9250/



(a) (b)

Fig. 4. (a) Wearable device in flexible form factor (b) Screenshot of the smartphone app used to control the device

activity produced by the muscles of the user. The sensors are connected to the MCU using an SPI interface, which makes it easy to interface additional sensors in future extensions. We plan to add more sensors such as galvanic skin response and blood oxygen sensor in future versions of the device. We note that adding new sensors may require changes in layout and power supply architecture on the device.

Communication: We use the integrated RF core in the TI CC2650 as the main communication module. It consists of a dedicated ARM Cortex-M0 to support communication tasks. The RF core can support the Bluetooth Low Energy (BLE) and ZigBee protocols using a 2.4 GHz RF transceiver. The BLE interface encrypts all the data that is sent over the air, thus ensuring the security and privacy of the user data. Moreover, BLE and Zigbee can be used to create a network of devices to make the platform scalable.

Energy Harvesting Unit: We use energy harvesting as the primary source of energy in our wearable platform to enable sustainable operation. In particular, we use solar energy harvesting with the help of a PV-cell, as shown in Figure 4. The PV-cell is connected to a maximum power point tracking charger that charges the Lithium-ion battery mounted on the device. The battery is used to store the harvested energy such that it can sustain autonomous operation when the harvested energy is below the energy requirement of the device [15].

Form factor: The base hardware can be manufactured in both rigid and flexible forms. Figure 4a shows the device in a flexible form factor. The flexible form factor is easy to wear as a patch on the body, which makes it comfortable to use for longer periods of time. We focus on incorporating a flexible form factor since flexible electronics technology has the potential to change the landscape in computing using stretchable and bendable platforms. Flexible hybrid electronics (FHE) [7] can enable powerful computing abilities in a stretchable and bendable form factor by taking advantage of the computing abilities of rigid processors. As a result, FHE technology allows us to perform local processing of TOMs, while maintaining a form factor that is comfortable and easy to wear as a patch. The rigid form factor is useful when a more rugged operation is required, such as mounting the device on a shoe. Both the form factors use PV-cells to harvest energy from the ambient light, fulfilling the energy harvesting requirement.

B. The Base Firmware

Operating System: The primary operating system consists of a thread-based, real-time operating system (RTOS) from Texus Instruments. The RTOS is responsible for scheduling and maintaining all the software tasks running in the system. The RTOS also provides drivers such as I2C, SPI, and UART to interface with the peripherals and sensors connected to the MCU. We employ the SPI interface to connect the motion sensors to the MCU.

Sensor API: The sensor API functions as the intermediate interface between low-level drivers and the application. In our software architecture, the sensor API provides functionality to control the sensors using the I2C or SPI interfaces. Specifically, it provides standard functions that allow the application to control the registers of the sensors and read data from each sensor. The modular nature of the sensor API interface allows the developers to easily add new sensors.

Communication services: The communication services consist of the BLE and Zigbee protocol stacks. The protocol stacks run on the RF core in the MCU, independently of the application. Whenever the application has to send data to another device, it sends a message to the stack which transmits the message over the air. All the data transferred using BLE and ZigBee is encrypted to ensure the security of the data.

Ease of development: We use the TI CC2650 MCU to ensure that tools needed for development of software for the wearable platform are easily accessible. Hence, *OpenHealth* users can use all the software tools available for the TI MCU. This includes software development kits, debugging kits, and RTOS libraries. In addition to the software tools provided by TI, we provide standard APIs to use the sensors in the *OpenHealth* platform. Finally, we plan to create a forum that will enable the users of the platform to discuss new applications, designs, and solutions to potential issues.

C. Public Release

The design files and firmware for the base platform are available for download at the *OpenHealth* web page[6]. In addition to HW design files, the public release also contains the base firmware that includes the RTOS, sensor API, communication libraries. To facilitate development effort and new research, we also include the reference applications presented in Section V, and anonymous data sets collected for these applications. Users of the wearable platform will also be able to upload new data sets, thus helping in the creation of a common data repository for movement disorders. We plan to maintain an *OpenHealth* Wiki-page that will describe the steps required for manufacturing the base platform and reference applications, as well as answering frequently asked questions.

[6]https://sites.google.com/view/openhealth-wearable-health/home

V. Example Application Domains

The *OpenHealth* platform can be used to implement a variety of wearable applications ranging from fitness tracking to continuous health monitoring of patients with movement disorders. One of our focus application areas is diagnosis and monitoring of patients with PD. For example, body motion analysis, response to therapy and motor fluctuation monitoring of PD can be achieved with 3-axis accelerometers and gyroscopes available in the base platform. This section illustrates two reference applications included with the *OpenHealth* release. Adding more sensors like sweat sensors, heart rate sensors and EEG can enable monitoring of nonmotor symptoms and progression [5]. A more detailed analysis of the data from wearable sensors and development of new algorithms for human activity recognition is left as future work.

A. Human Activity Recognition (HAR)

One of the first steps in the treatment of movement disorders is to understand what the patients are doing [3]. This objective is achieved through HAR algorithms, which aim to identify the user activity, such as, standing, walking, and jogging, by processing sensor data. Since efficient HAR implementations can provide valuable insights to both health professionals and patients, we include it as one of the two reference applications. To implement our HAR application, we employ the base platform, which contains the MPU-9250 motion sensor, along with a wearable stretch sensor [1]. We use a combination of accelerometer and stretch sensors since it provides 10% higher recognition accuracy than using either sensor alone. The 3-axis accelerometer in the motion sensor is placed near the ankle to capture the swing of one of the legs. The stretch sensor is used on a knee sleeve to capture the degree of bending of the knee. During this work, we performed 58 unique experiments with 9 users and collected data for the activities summarized in Table I. Then, the data is used to train a programmable neural network that can recognize these activities in real-time. A sample snapshot that contains the data for *Stand, Jump, Walk,* and *Sit* activities is shown in Figure 5. Our experimental evaluation shows that we achieve an accuracy greater than 90% for all the activities, as shown in Table I. The application consumes about 12.5 mW power for recognizing a single activity. *The user data as well as the implementation of the HAR application will be included in the OpenHealth release*.

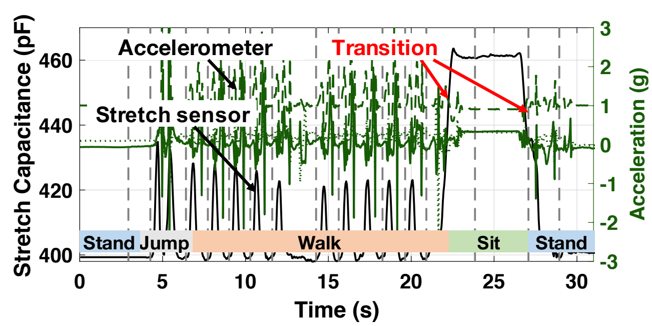


Fig. 5. Sequence of activities in the HAR application

TABLE I
ACCURACY OF THE HAR APPLICATION

Activity	# Correct / # Total Segments	Accuracy (%)
Drive	154 / 155	99.4
Jump	169 / 181	93.4
Lie Down	204 / 204	100
Sit	385 / 394	97.7
Stand	345 / 350	98.6
Walk	794 / 806	98.5
Transitions	115 / 127	90.5

B. Gesture Recognition

Gesture recognition is another application that is very useful in the context of health monitoring. Gesture recognition can be used in applications such as gesture-based control and interaction with assistive devices. We implemented a gesture recognition application that uses the accelerometer sensor in the base platform. The device is mounted on the wrist of the user to record the accelerometer data when the user is performing a gesture. Using a NN classifier, our application recognizes gestures, such as *up, down, left* and *right*, which can be used to control assistive devices. Experimental evaluations using seven users show that the wearable device can recognize gestures with an accuracy of 98.6% while having an active power consumption of about 10 mW. Our implementation of the gesture recognition application [14] and the corresponding data set is available with the release of the wearable device.

VI. Conclusion and Future Directions

This paper presented the *OpenHealth* platform for open source health monitoring. It discussed the need for wearable health monitoring and the challenges faced by wearable devices before their widespread adoption. Then, it presented the hardware and software details of the *OpenHealth* platform. Finally, we provided example applications for human activity and gesture recognition using the proposed wearable platform.

In order to assess whether the wearable device is able to address the challenges and meet our vision, we will conduct extensive user studies with movement disorder patients. We also plan to design custom SoC with reconfigurable NN accelerators to reduce the power footprint into μW range. Furthermore, we will integrate additional modalities of energy harvesting such as body heat and body motion. These will be key enablers to sustainable and maintenance free operation.

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