This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2017.2776351, IEEE Journal of Biomedical and Health Informatics

IoT-based Remote Pain Monitoring System: from Device to Cloud Platform

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***Abstract*—Facial expressions are among behavioral signs of pain that can be employed as an entry point to develop an automatic human pain assessment tool. Such a tool can be an alternative to the self-report method and particularly serve patients who are unable to self-report like patients in the Intensive Care Unit and minors. In this paper, a wearable device with a bio-sensing facial mask is proposed to monitor pain intensity of a patient by utilizing facial surface electromyogram (sEMG). The wearable device works as a wireless sensor node and is integrated into an Internet of Things system for remote pain monitoring. In the sensor node, up to eight channels of sEMG can be each sampled at 1000 Hz, to cover its full frequency range, and transmitted to the cloud server via the gateway in real-time. In addition, both low energy consumption and wearing comfort are considered throughout the wearable device design for long-term monitoring. To remotely illustrate real-time pain data to caregivers, a mobile web application is developed for real-time streaming of high-volume sEMG data, digital signal processing, interpreting, and visualization. The cloud platform in the system act as a bridge between the sensor node and web browser, managing wireless communication between the server and the web application. In summary, this study proposes a scalable IoT system for real-time biopotential monitoring and a wearable solution for automatic pain assessment via facial expressions.**

***Index Terms*—Pain assessment, Healthcare Internet-of-Things (IoT), Biopotential sensor node, Wearable sensors, Cloud computing, Web-based UI for IoT applications**

I. Introduction

REMOTE health monitoring systems in hospital or home are required to reduce the overall healthcare cost and optimizing healthcare processes and work-flows [1]–[3]. Pain is among the key remote monitoring indexes as a vital indicator in disease diagnosis and relieving the discomfort of patients. Some telehealth research efforts have been made through telephone-based, web-based or mobile application questionnaire answered by patients themselves across various patient groups [2], [4]–[7]. The questionnaire includes pain intensity in visual analog scale, pain location, and medications for patients at home. Results from these studies indicate that such remote pain monitoring and feedback system is feasible and effective in monitoring daily pain state. However, there are several constraints in the self-report methods. People's non-compliance to manual entry of daily information, especially in long-term monitoring, is one of such issues [2]. The second limitation is that such methods are not suitable for the group of people with limited cognition and expressing abilities, such as neonates, elderly, and sedated patients in Intensive Care Unit (ICU). The third shortcoming of conventional approaches lies in the lacking of an efficient way providing patients with continuous and real-time pain state monitoring. As a result, patients are exposed to severe and long-lasting pain due to delayed access to medical treatment and prolonged waiting time. These were the rationale behind the recent studies on objective and automatic pain intensity monitoring methods.

Some efforts have been devoted to achieving automatic pain assessment, either from the approach of facial expression recognition in face video [8] or physiological signal fusion [9]. However, there exist limited efforts in integrating automatic pain assessment with remote health monitoring systems [10], [11]. In this paper, both cloud and Internet of Things (IoT) technologies are leveraged to propose an automatic pain assessment tool for remote patient monitoring systems. The system proposed in this paper is targeted for inpatients and ICU patients, utilizing a novel pain intensity detection tool as an alternative to face video.

The pain intensity detection tool proposed in this study detects and evaluates pain from facial expressions by

This research was supported in part by Fundamental Research Funds for the Central Universities, and the Science Fund for Creative Research Groups of the National Natural Science Foundation of China (Grant No.51521064).

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monitoring facial surface electromyography (sEMG). The facial muscle activities are monitored by a facial mask embedded with surface sensors which can be developed into a wearable device and further integrated into a remote monitoring system. In addition to the proposed pain assessment tool, a remote pain monitoring system is presented in this study. The proposed system has the function of multi-channel biopotential data acquisition, wireless data transmission, signal processing and remote data visualization. The proposed system involves both sensing devices and a cloud-based back-end supporting patients who have access to Wi-Fi hotspot and caregivers using a computer or a smart device with web browsing feature. The cloud-based back-end enables the system to be extendable with advanced data analytics such as big data processing and deep learning. To summarize, the main contributions of this article are as follows:

- proposing a wearable bio-sensing mask for capturing facial expression in pain monitoring application.
- designing a low-power and miniaturized eight-channel biopotential sensing and processing module with Wi-Fi data transmission.
- developing a cross-platform interactive mobile web application for recording, processing, interpreting, and visualization of the biopotential data stream.
- implementing a cloud-based platform with data storage and web server, customized for high data rate streaming IoT applications capable of synchronizing data with the web application.
- evaluating the pain states using multi-channel facial sEMG.

The rest of the paper is organized as follows. In Section II, literature review and requirement analysis are stated from the device and system viewpoints. Section III illustrates the application scenario, remote pain monitoring in the hospital. System architecture and its elements are also presented in the same section, covering all the components including the wearable sensor node, gateway, cloud server and the mobile web application. Section IV then presents the implementation of each component in detail. System evaluation is presented in Section V, while Section VI concludes the paper.

II. Motivation and Related Work

This study is motivated by the fact that a growing demand for automatic pain assessment arises in hospitals to improve the quality of care for patients and also to facilitate the work-flow for medical staff. Facial expression is among the behavioral signs in pain assessment tool for patients unable to self-report, and thus it is taken as an index of pain in the remote pain monitoring system. To meet the requirements of multi-channel biopotential acquisition and transmission in an IoT framework, the concept of a wearable sensor node for pain monitoring is proposed. A corresponding IoT architecture with a mobile web application is meanwhile customized for biopotential processing and pain remote monitoring.

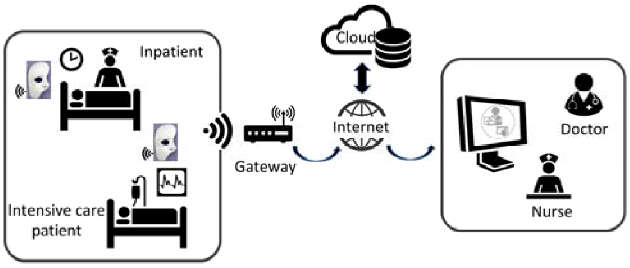

Fig. 1. Remote pain monitoring in hospital for inpatients and ICU patients

In terms of pain related facial expressions, five facial muscles (corrugator, orbicularis oculi, levator, zygomatic and risorius) are involved in adults [12]. Existing wearable or portable sEMG devices are application specific for limb muscles [13], [14] and bulky in size which is not proper for tiny muscles. Moreover, the sensor is usually designed in separate channels when having the function of wireless data transmission. A wearable facial EMG device has been designed in [15]. It estimates the user's positive or negative emotion from two channels of EMG on one side of the user's face, while facial expressions of pain involve more facial muscles such as levator and risorius. A compact and unobtrusive multiple-channel sEMG sensing device is therefore designed in this study to measure the activity of tiny facial muscles for pain assessment application. Furthermore, the captured sEMG signal can be then processed and displayed in real-time with the support from the system.

There are several concerns in designing the wearable sEMG device, and the first one comes with biopotential signal quality. Electrode to skin contact impedance is one parameter relates to signal quality, where high impedance could cause weak conductivity between the electrodes and the skin and therefore degrade the signal to noise ratio and electrolyte gel is usually used to reduce such impedance [16]. In addition, biopotentials are prone to be corrupted by electrical interference coupled to the human body and unshielded lead wires particularly when lead wires are long [17], [18]. This issue is usually solved by applying 50 Hz or 60 Hz notch filter to raw samples. The second technical concern is the power consumption of the sensor node as a battery powered device. From the system point of view, data processing can be done on the sensor and then the results are sent to the server [19], [20], or alternatively, original data is transmitted to the fog/cloud server for processing [21]–[23]. The latter case may save energy for the device and help reach a balance between device energy consumption and transmission delay. Besides those technical concerns, comfortableness is also one key point in designing a wearable device.

To monitor biosignal stream from the caregiver end user's perspective, web service is a solution to real-time or near real-time data visualization in an IoT platform [24], [25]. Compared with developing a web application or a mobile application for a single platform, a hybrid application is more interoperable and can be used across multiple mobile platforms such as

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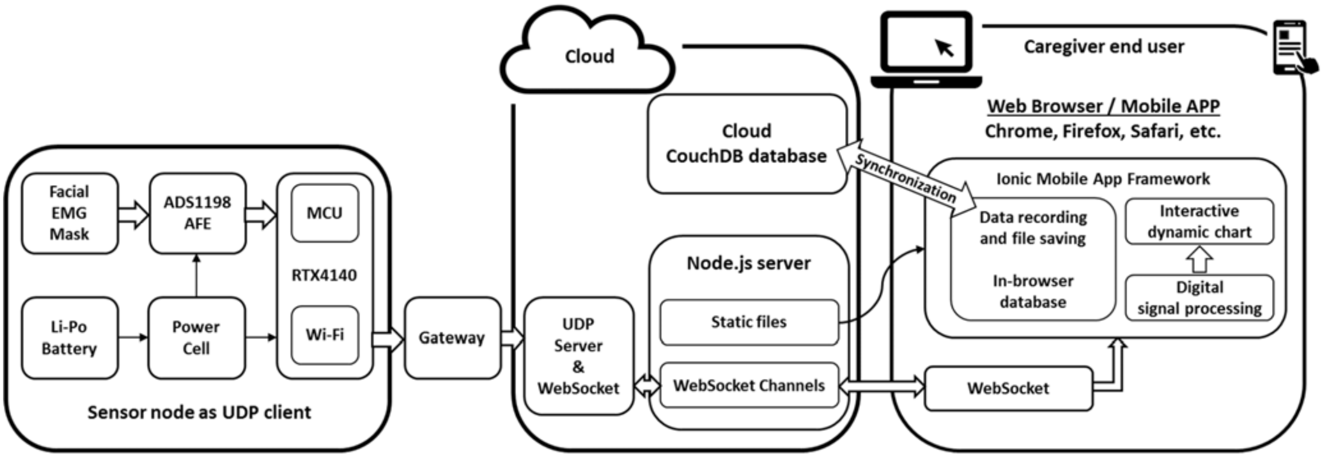

Fig. 2. The structure of IoT-based biopotential measurement system and cloud-based data flow in the automatic pain monitoring system

Android, iOS, Windows Phone, and Blackberry where the web application runs in mobile browsers [26]–[28]. Therefore, the mobile application in this work is built on a Hybrid Mobile App UI framework.

III. Remote Pain Monitoring System

The IoT-based remote pain monitoring application and its architecture are shown in Fig. 1, which is designed for the real-time central monitoring of inpatients and intensive care patients in the hospital. It is composed of four parts:

1) Wearable sensor node

The sensor node is composed of a passive sEMG sensor facial mask and a sEMG sensing and processing module. The mask is built on a soft and stretchable material. It is replaceable after use. While the hardware module is reusable responsible for biosignal conditioning, digitalization, and wireless data transmission. The electrodes integrated on the inner side surface of the mask are closely attached to the facial skin for reliable sEMG measurement. The placement of the electrodes is determined by the targeted facial muscles. Due to the soft nature of the implemented mask, the electrode position and the shape of the mask can be slightly adjusted accordingly to accommodate individual facial differences.

2) Gateway

As the intermedia between sensor nodes and cloud, the gateway can be a general router, the personal hotspot of a cellphone, or a smart gateway supporting with added features such as heterogeneity, scalability, and reliability. The system can benefit from smart gateways especially when heterogeneous data and communication technologies exist in the overall healthcare remote monitoring system.

3) Cloud server

The cloud server receives data from the sensor nodes with UDP or TCP protocol, then forwards to a data streaming channel which can be connected to another database server for storage and any device with an HTML5-enabled web browser. This server model is compatible with cloud computing models such as Software as a Service (SaaS) and Platform as a Service (PaaS), which could be a key advantage for further signal processing and data mining, as well as implementing flexible data privacy policy.

4) Mobile web application

In this architecture, an HTML5-based mobile application acts as an interactive interface between system and caregivers. It can render real-time waveform, conduct lightweight algorithms, save data to an in-browser database and synchronize with the remote database servers. The web browser based application is a client-server software application, in which the user interface runs in a web browser. One advantage of the web app is that it can be widely applied to various terminal devices. In general, it is a cross-platform app, compatible with mainstream operating systems, such as MS Windows, Mac OS, and Android. The implemented web app is capable of running on any terminal devices equipped with a web browser, including stationary terminals and mobile devices.

IV. Device Design and System Implementation

The implemented IoT based pain monitoring system can be divided into three main functional parts, as shown in Fig. 2. The first part is a wearable sensor for multi-channel sEMG acquisition, which includes a biopotential acquisition sensor node and a wearable bio-sensing mask. The sensor node also works as a UDP client transmitting data to the cloud through the gateway. The second part of the implementation is the cloud server, which is in charge of wireless data transmission from the sensor node to remote caregivers by using UDP communication and websockets. Moreover, it also contains the node.js server for the mobile application and a database for synchronizing the recorded data files selected by end users, caregivers. The third part is web application embedded with digital signal processing. It includes dynamic sEMG waveform display on devices across operating systems. The entire system implementation and data transmission flow are illustrated in Fig. 2. The details of each part are presented in the subsections below.

A. Wearable sensor design for pain monitoring

The sensor node is first designed to meet the data acquisition and transmission requirement considering the data rate of sEMG. Then the whole sensor node is integrated including functional modules, battery power supply, and skin-friendly device packaging. Another part of the design is a facial mask embedded with passive electrodes for wearable use. The facial mask together with the sensor node constitutes the wearable sensor monitoring facial sEMG.

1) Sensor node design for biopotential acquisition

As a continuously running wearable device, low power consumption is taken into consideration during the design process. Therefore, a low power analog front end (AFE) ADS1198 [29] is chosen for biopotential measurement, which is an eight-channel AFE with 16-bit analog to digital resolution and a programmable gain from 1 to 12. The sampling rate of each channel is programmable and is set to 1000 samples per second (SPS) to cover the full bandwidth of sEMG signal [30] according to the Nyquist sampling theorem. The gain is set to be 12. So the data rate with full channel transmission is 128 Kbps at a minimum. RTX4140 Wi-Fi module [31] is utilized due to SPI communicating with ADS1198, its Wi-Fi functionality and its outstanding power performance among low power Wi-Fi Modules [32]. On the basis of these two modules, the sensor node is implemented by hardware design and software co-design using Co-Located application framework in the Micro Controller Unit of RTX4140.

2) Sensor node integration

Since the proposed wearable device will be finally attached on a user's face as a soft mask, considerable efforts are made to address the user experience issues. Ideally, the skin-attached sensing devices should be miniaturized, unobtrusive, and long lasting in nature. Considering the implemented mask-like device is design for continuous pain status monitoring, several practical issues have been taken into consideration during the prototype design from the aspects of users' comfortableness prototype is implemented on flexible printed circuit board which is bendable to fit the curve of a human's face naturally. Electronic modules and peripheral components are mounted on the front side of the flexible printed circuit board while a coin battery and electrode interface are mounted on the back side. The dimension of the implemented electronic core module is around 30 mm × 60 mm, as shown in Fig. 3.

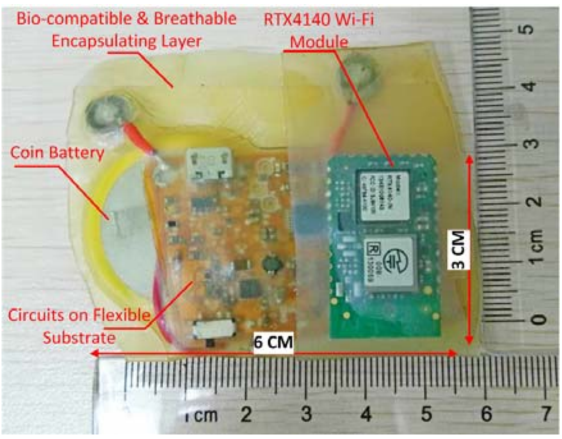

Fig. 3. Miniaturized flexible sEMG sensor encapsulated by a thin waterproof dressing

TABLE I
FACIAL MUSCLES UNDER MONITORING AND THE TARGETED FACIAL ACTION UNITS

Channel	Muscular basis	AU
1	Frontalis	
2	Corrugator	Brow lower (AU 4)
3	Orbicularis oculi	Lids tighten (AU 6)
		Cheek raise (AU 7)
4	Levator	Nose wrinkle (AU 9)
		Upper lip raiser (AU 10)
		Eyes close (AU 43)
5	Zygomatic	Lip corner pull (AU 12)
6	Risorius	Horizontal mouth stretch (AU 20)

In addition, in most cases, constant exposure to moisture and water, e.g. sweat, is one of the leading causes of electronic failure in wearable devices. The same applies to the implemented mask sensor proposed in this paper. A further enhancement is needed during integration process to protect the inner electronic components against moisture and water. One straightforward and efficient approach is to encapsulate the electronic components by using waterproofing thin dressing materials. 3M Tegaderm adhesive dressing is adopted to encapsulate the electronics modules while leaving openings for the electrode interface and battery socket on the back side. The encapsulating layer is very thin (with the sickness of 0.46 mm), yet highly absorbent, with excellent vapor permeability. The thin dressing is semi-transparent, allowing the observation of the inner condition of the electronics and the running status of the device, e.g., the blinking of LED for status indication. By applying the thin dressing layer over the electronic parts, the device's mechanical and electrical reliability is further enhanced, in the meantime, making the device waterproof yet with excellent moisture permeability. As shown in Fig. 3, the implemented flexible sensing device is thin and bendable addressing on user comfortableness issues. It will serve as the core module of the proposed smart mask for remote pain monitoring.

B. Wearable bio-sensing facial mask

The main facial muscles under monitoring are listed in Table I. Most of the muscles are involved in one or several facial action units (AU) in Facial Action Coding System [33] as pain behaviors [12]. To monitor the activities of these facial muscles, passive electrodes are placed on one side of the face following Fridlund and Cacioppo Guidelines [34].

Fig 4(a) shows the concept of the facial mask, which includes two parts, sensor node, and soft facial mask. The sensor node part is to, condition, digitalize and wireless transmit sEMG signal, as mentioned above. The soft facial mask part is to capture multiple channel sEMG. To work compatible with the sensor node, the soft facial mask integrates electrode leads as the connection between electrodes and the sensor node in addition to the conductive electrodes for capturing sEMG signal. Six biopotential channels are employed on the mask to monitor six facial areas in a monopolar configuration. In the monopolar configuration,

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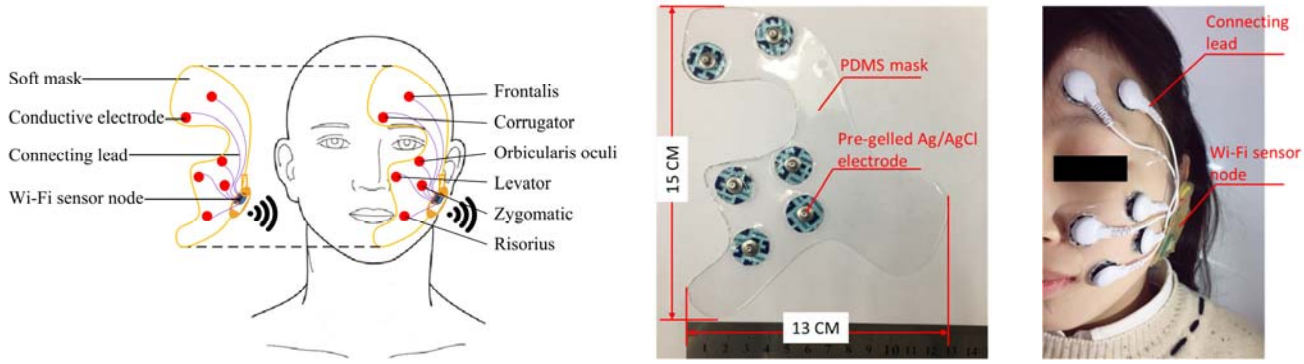


(a) Design concept of the facial mask (b) Electrode embedded facial mask (c) The complete wearable device

Fig. 4. Design concept of the facial mask

each channel of biopotential is captured with respect to the common reference electrode placed on the bony area behind the ear. In this way, the number of electrodes and connecting leads is reduced compared to a bipolar configuration where both differential input electrodes to an amplifier are placed near to each other in the same facial area.

The proposed mask is implemented by integrating the detecting electrodes into soft polydimethylsiloxane (PDMS) substrate. As a result, the designed mask is easy-to-apply, and one-step solution, which can largely save the valuable time of the caregivers when making setting up for sensing vital bio-signals from patients, in particular in the ICU ward environment. The implementation of the facial mask design is presented in Fig. 4(b). The customized facial mask is based on transparent polydimethylsiloxane (PDMS) material. The softness of PDMS makes the mask fit well on the curvature of the user's face. The thickness of the manufactured mask is 100 µm. In the process of molding the mask, six pre-gelled Ag/AgCl electrodes are placed on the molding substrate and therefore embedded in the mask. The mask with embed electrodes weights 7.81 g in total, as shown in Fig. 4(b). Since the PDMS substrate is soft and stretchable which makes it favorable for deforming the shape of the mask and adjusting the electrode positions to the corresponding detection points on patient's face. As a result, the implemented mask is easy-to-apply, and one-step solution, which can largely save the valuable time of the care givers for vital bio-signals measurements in the ICU ward environment.

Finally, the entirety of the pain assessment tool is presented in Fig. 4(c) with the integrated Wi-Fi sensor node attached behind the ear, the electrode-embedded PDMS facial mask and the leads connecting these two parts. The overall weight of the implemented pain assessment tool is 39.08 g, which is light and causes little burden to the user in long-term use.

C. Mobile web application design

When choosing the framework and database for the application, the capability of holding big healthcare data stream and real-time analytics is considered. The mobile web application is built upon Cordova and Ionic framework, which support different mobile platforms including Android and IOS by offering a unified web programming interface based on HTML5, CSS, and Javascript. Cordova also enables hardware access in Javascript, such that Bluetooth chip can be reached within the app. A library named Socket.io with WebSocket support is introduced for fast real-time bi-directional communication between the web server in cloud and the client in browser. Data can be locally saved in an in-browser NoSQL database powered by PouchDB, which also enables offline usage of the app. Data can also be synchronized to the cloud CouchDB database for sharing and analyzing. The recorded data can be exported as a text file and presented as waveforms in the dashboard, features such as digital filters, interpretation and down-sampling are also provided. Considering data security and privacy issues, username and password are required for the login on the remote terminal devices. In addition, Web-Socket secure (Web-Socket over TLS) is applied between the mobile terminal devices and the cloud server which further enhances the security for data transmission.

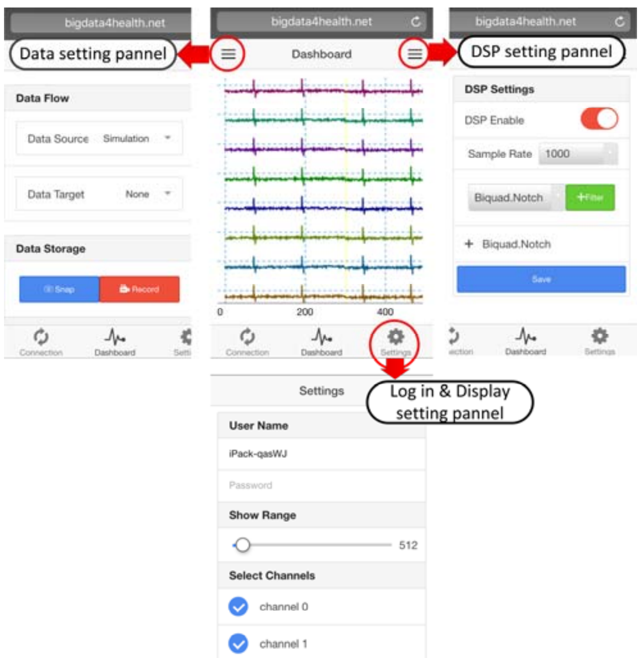
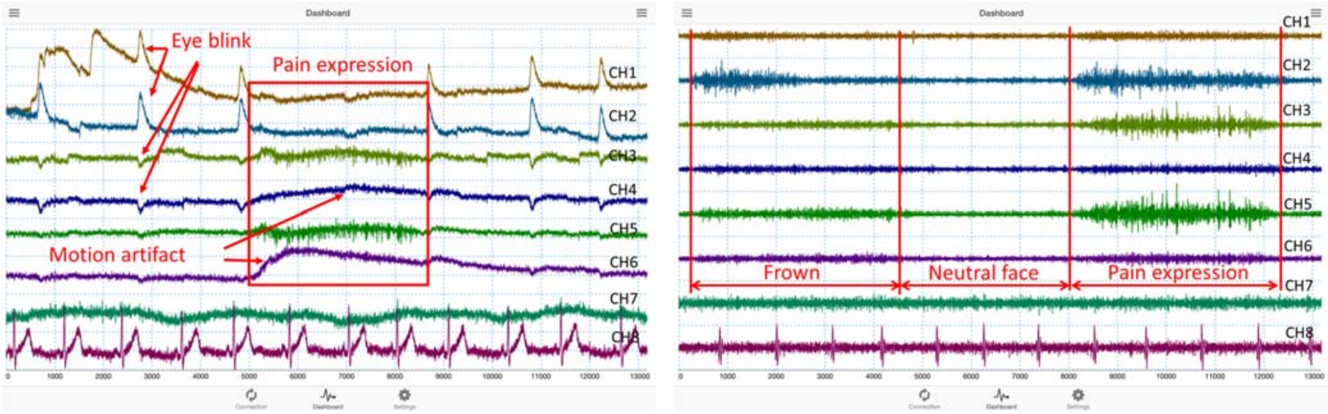


Fig. 5. The dashboard and its setting panels



(a) Raw biopotentials (b) With on line filtering

Fig. 6. Dashboard displaying eight channel biopotentials

The web-based graphical user interface (GUI) on a mobile phone is presented in the middle of Fig. 5 together with its three setting panels. The achieved functions include 1). Data settings, where data source can be chosen to present in dashboard and start-stop data recording; 2) Log in & display settings, where username and password are required to ensure user privacy; and 3) Digital signal processing (DSP) settings, which is for digital filter configuration such as sample rate, filter type, and window function.

The web-based GUI can display the collected bio-signals in a near real-time manner. Since the web-based GUI is cross-operational-system, it is stand-alone and can run on any internet-connected terminal device equipped with a web browser, including smartphone, laptop and mobile/tablet PC. Cloud-storage and cloud-computing functions are also designed and merged into this application, which enables people with authority get access to the data of interest anywhere in the world. In addition, algorithms running on the cloud server facilitate the near-real-time signal processing or post-analysis. The dashboard of the web application presents the measured multi-channel sEMG signals in near real time, depending on the researcher or physician's requirements. Processed signals can also be displayed after a set of cloud-based filters or algorithms being applied.

There are several benefits applying cloud-based on-line filtering comparing to implementing signal processing on the device. Firstly, onsite processing may cause extra latency and energy consumption due to the extra computation involved. Secondly, onsite processing requires the filtering algorithms to be solidified into the chipset of the sensing device, which is inconvenient or impossible for the re-program or dynamic adjustment of the filtering parameters on demand in real time. Thirdly, it is more flexible to adjust the filters or algorithms setting on the user end in the mobile web application than in the sensing device. This could be more attractive for medical researchers or professionals to dig out information valuable to them using the algorithms developed by their own.

V. System Verification and Device Summary

One test subject was involved in the test and was guided to perform a series of facial expressions. Three facial expressions were defined in the test, and they were 1) neutral face as a blank expression, 2) frown as slight pain which is also common to express several other negative emotions and 3) pain expression with a combination of AUs in Table I such as cheek raise, nose wrinkle, and horizontal mouth stretch. The device is capable of measuring up to 8-channel biopotential signals, where 6 channels are measured EMG signals from patient's face, with measuring points indicated in Table I. Channel 8 is utilized for electrocardiogram (ECG) monitoring which is a vital sign for ICU patient, with the electrode placed in the infraclavicular fossa. Channel 7 is saved as spare channel for further measurement extension. Each channel has one electrode placed on the measurement site. The biopotential is measured by the reference to the common electrode which is placed on the bony area behind the ear on the same side. Multi-channel biopotentials are captured, transmitted to the cloud platform and eventually their waveforms are presented in the web application in a near real-time manner. The recorded biopotential samples in the test are then downloaded for post-analysis.

A. Biopotential acquisition and remote monitoring

The monitored multi-channel biopotentials are shown in Fig. 6. The waveforms are updated on the dashboard in a laptop web browser. Waveforms without and with on-line filtering are presented separately. Fig. 6(a) shows the 6 channels of sEMG waveforms collected from the test subject's face and 1 channel ECG without digital signal processing. The raw data received in the cloud server is displayed on the dashboard. It can be observed that a few concurrent spikes and reversals occur at the same time from Channel 1 to Channel 6. The eye blink interference in sEMG is triggered by eyelids movement, where the first two channels are dominated by upper eyelid and Channel 3 to Channel 6 reflect lower eyelid movement. As a result, the eye blinks are captured in Channel 1 and Channel 2 as rising pulses, while the concurrent signals in Channel 3 till

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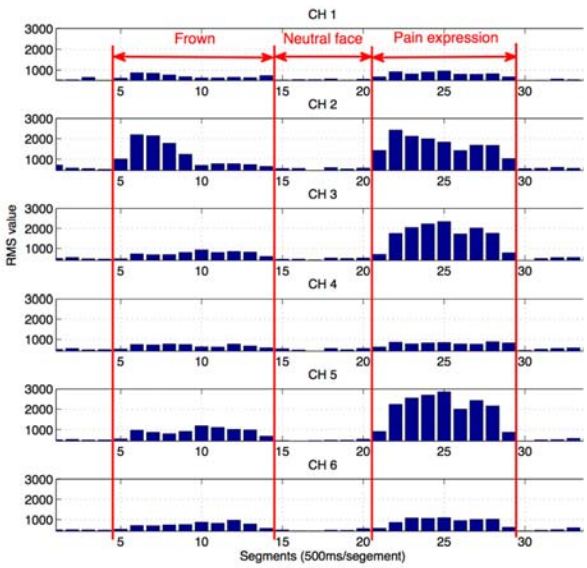

Fig. 7. RMS features of collected samples in 500 ms segments

Channel 6 are transient sharp declines. In addition, it can be found that the dips in Channel 5 and Channel 6 are much smaller than those in Channel 3 and Channel 4 because of locating further lower from eyelids. During blink, the muscle groups around eye sides make simultaneous contractions towards the eyeball, which means the orientation of the biopotential signals measured from the forehead is opposite to its counter parts measured from the points below the eye. Shown in Fig. 6(a), the eye-blink captured and shown in Channel 1 and Channel 2 are rising pulses, while the concurrent signals captured in Channel 3 till Channel 6 are transient sharp declines. In addition, it can be found that the dips in Channel 5 and Channel 6 are much smaller than those in Channel 3 and Channel 4 because of locating further lower from the central muscle group around the eye.

Facial activities in the pain expression can be clearly differentiated from the neutral expression although no signal processing is applied. The sEMG signal is dominant in the frequency range of 50 - 150 Hz [35]. While baseline wander and motion artifact, as shown along with sEMG signal are caused by body or muscle movements and in low-frequency range below 20 Hz. Since the offending artifacts obscure the target sEMG signals in study, digital filters can be applied to remove the interference. A high pass filter of 20 Hz can efficiently suppress the baseline wander noise and remove motion artifacts. Besides, the high pass filter removes eye blink pulses from the signal at the same time. A second digital filter is added to remove powerline electrical interference, which is a 50 Hz notch filter. The digital filters were implemented in the mobile web application using 4^{th} order Butterworth filters. Butterworth filter was chosen for its flat frequency response in the passband.

By leveraging cloud resources and web application, digital signal processing is available in a real-time manner and the filtered samples are shown in Fig. 6(b). In the first facial expression, muscle activity of corrugator in Channel 2 is observed due to frowning. It is followed by a neutral face and then a facial expression of pain. In Neutral Face section, the test subject remains calm; as a result, all sEMG channels keep quiet. In Pain expression section, the test subject mimics suffering from acute pain where facial muscles groups are actively simulated for a few seconds. As can be observed in Fig. 6(b), Channel 2, 3 and 5 record significant facial muscle response. The time axis in the dashboard is in milliseconds (ms) and the peak to peak amplitude of sEMG is in a few millivolts after amplification in sensor node.

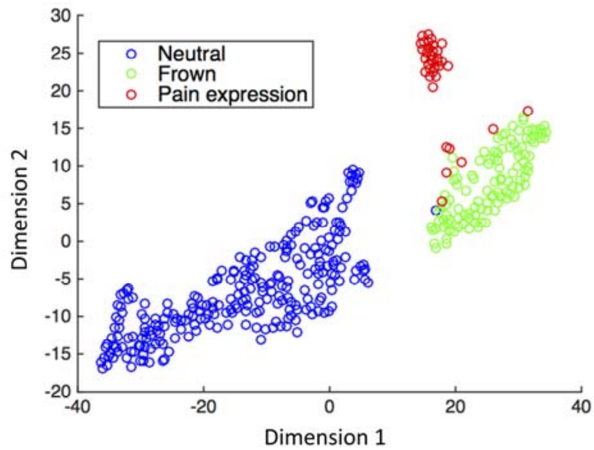

Fig. 8. The distribution of RMS features

B. Post data analysis

Raw sEMG signals in the test are saved in file for further offline analysis. The pattern of facial expressions in sEMG is revealed by root mean square (RMS) feature extraction and feature visualization. The feature RMS indicates the energy level of the signal. Samples in time series are first filtered and segmented, then RMS can be calculated from each segment. Fig. 7 shows the RMS out of the first six channels sEMG in Fig. 6(b), where the signal is cut into 500 ms segments. The distribution of the RMS features from the test is shown in Fig. 8 after dimension reduction with t-Distributed Stochastic Neighbor Embedding technique [36]. A k-NN classifier (k=5) was trained and tested with the RMS features. The classification accuracy in the 10-fold cross validation is 95.9%.

C. Device summary

This remote pain monitoring system centers on the sensor node from the patient end. Cloud and the designed mobile web application assist in taking over the collected biopotentials automatically and remotely. The implemented wearable IoT device together with the back-end cloud architecture as a whole can provide the users not only the online signal processing and data storage functions, but also data visualization and graphical interacting interface solution. Key features of the designed sensor are summarized in Table II. The designed sensor node is aiming at minimized size with full function of biopotential data collection and Wi-Fi wireless transmission. It reaches the size of 60mm × 30mm as a flat and soft module, for 8 channel biopotential collection at 1000 SPS. Energy efficiency is fully addressed by using ultra low power electronic components and cutting down the radio frequency power consumption by triggering wireless data transmission into burst mode. The applied biopotential measurement AFE chipset (including

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TABLE II
SUMMARY OF BIOPOTENTIAL MEASUREMENT SENSOR NODE

Attribute	Value
Size	60mm×30mm
Sampling parameters	8 channels, 1000 SPS sample rate, 16-bit
Data rate	128 Kbps
Power consumption	Total power consumption: 18.6 mW Biopotential measurement: 8.2 mW Wi-Fi module supply voltage: 3.5 V --Listening interval: 1000 ms Wi-Fi module supply current: 0.76 mA --Listening interval: 100 ms Wi-Fi module supply current: 2.6 mA

ADC) is at the power of 8.2 mW once the sample rate set to 1000 SPS. The Wi-Fi module together with the embedded microprocessor consumes only 9.1 mW with listening interval of 100 ms. The power consumption of the whole device once running in the normal working status is measured as 18.6 mW in total.

VI. CONCLUSION

This paper presented a design of a wearable bio-sensing device for biopotentials monitoring in up to eight channels. With a wearable facial mask, the device is capable of collecting sEMG from several facial muscles simultaneously. The design can be applied in pain assessment when monitoring facial expressions as a behavioral sign of pain. Both the sensing facial mask and the sensor node are potential for long-term use because both wearing comfortableness and low energy consumption are considered and qualified in the design. Furthermore, the wearable device works as a Wi-Fi sensor node, integrated into an IoT system for remote monitoring use. The IoT-based remote monitoring system is scalable in terms of devices and functionality due to the sensor-gateway-cloud architecture. In the implemented system, the cloud platform enables mobile web applications so that caregivers are able to reach the interactive GUI for biopotential monitoring across operating systems. Moreover, the cloud platform provides room for any further implementation of online data analysis and decision-making support algorithm for the pain management application. The implemented system is also applicable to other healthcare applications where biosignals need to be monitored in the near real-time manner.

ACKNOWLEDGMENT

The authors would like to thank Gaoyang Pang for his work developing PDMS based mask and Jia Deng for her volunteer work as a test subject.

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JBHI.2017.2776351, IEEE Journal of Biomedical and Health Informatics

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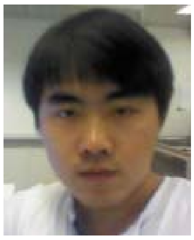

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