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IoT-based Remote Facial Expression Monitoring System with sEMG Signal

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***Abstract*—Biopotentials including Electrocardiography (ECG), Electromyography (EMG) and Electroencephalography (EEG) measure the activity of heart, muscles and brain, respectively. They can be used for noninvasive diagnostic applications, assistance in rehabilitation medicine and human-computer interaction. The concept of Internet of Things (IoT) can bring added value to applications with biopotential signals in healthcare and human-computer interaction by integrating multiple technologies such as sensors, wireless communication and data science. In this work, we present a wireless biopotentials remote monitoring and processing system. A prototype with the case study of facial expression recognition using four channel facial sEMG signals is implemented. A multivariate Gaussian classifier is trained off-line from one person's surface EMG (sEMG) signals with four facial expressions: neutral, smile, frown and wrinkle nose. The presented IoT application system is implemented on the basis of an eight channel biopotential measurement device, Wi-Fi module as well as signal processing and classification provided as a Cloud service. In the system, the real-time sEMG data stream is filtered, feature extracted and classified within each data segment and the processed data is visualized in a browser remotely together with the classification result.**

***Keywords*—Biopotentials, sEMG, Healthcare Internet of Things, Remote Patient Monitoring, Facial Expression Recognition.**

I. Introduction

Facial expression recognition is studied across several fields such as human emotional intelligence in human-computer interaction to help improving machine intelligence, patient monitoring and diagnosis in clinical treatment. For instance, users' spontaneous facial expressions can be taken as indicator when they are confronted with computer-related issues and be used to show students' reaction in educational game [1, 2]. In clinical applications such as pain assessment, facial expressions are considered as behavioral signs of pain in patients regardless of their age [3]. Facial surface Electromyography (sEMG) is the electrical potential generated by muscle cells and captured by surface electrodes. It has high temporal resolution and sensitivity in detecting facial muscle activities. Compared with facial image processing method, the superiority of facial sEMG method is its unconstraint by lighting condition and head pose as well as its potential for wearable or portable devices [4].

Remote patient monitoring is an emerging application in healthcare exploiting from the concept of Internet of Things (IoT) and body area network, where sensors and things are connected to the network thanks to the recent advancements in information and communication technology. Biopotentials such as Electrocardiography (ECG), EMG and Electroencephalography (EEG) in a real-time remote monitoring system need to be processed after acquisition. Signal processing with biopotentials includes power line interference, baseline drift and movement artifact denoising, and feature extraction in time domain or in other domains. Machine learning can be also added to enhance machine intelligence according to application requirements. In a typical IoT platform consisting of smart device (sensors) layer, Fog (smart gateways) layer, and Cloud layer, biopotential signals can be potentially processed on any of these layers, or collaboratively on more than one layer depending on the complexity of the demanded computation. However, for computationally intensive applications, Cloud is more preferred.

There are various methods for classification and biopotential signal processing which include signal transformation so as to explore lower information loss as well as more diverse feature extraction and higher classification performance. For instance, wavelet analysis is widely applied on denoising and feature extraction. However, biopotential signal processing together with classification is generally implemented on an off-line computer using datasets rather than in an on-line fashion on data streams such as multiple channel sEMG where high data-rate is demanded for a remote IoT-based health monitoring system. Thus, we not only integrate high data-rate biopotential measurement devices into our IoT-based system, but also employ on-line biopotential signal processing and classification. Only essential extracted information and classification result are visualized for end-users.

In this paper, we present a remote facial expression monitoring system which i) acquires multi-channel high data-rate facial sEMG signals, ii) utilizes Wi-Fi wireless communication to transfer data streams, and iii) exploits Cloud computing for heavy signal processing. In our platform, four channels of unipolar sEMG signals are gathered to differentiate four preset facial expressions, and a multivariate Gaussian classifier is trained for data streaming classification. The architecture and implementation of the system can be also reused for other applications requiring multi-channel biopotential measurements with a comparatively high data rate. In summary, our main contributions are as follows:

- proposing a multi-channel biopotential IoT-based remote monitoring system with Cloud-based signal processing
- demonstrating the full system in a prototype on a case study of facial expression recognition with sEMG signals

The rest of this paper is arranged as follows: In Section II, we summarize the general sEMG acquisition and processing procedures and review some former studies on facial expression recognition system and sEMG remote monitoring system; Section III first introduces the proposed architecture then explains its main components and the data transmission flow in it; Section IV presents our implementation based on the architecture; In the end, Section V concludes the paper.

II. RELATED WORK

sEMG signal pattern recognition is studied in facial expression recognition with facial sEMG as well as hand gesture recognition with sEMG from upper limb muscles. They both have great potentials in the human-computer interaction field and have been utilized in different applications such as myoeletrical control system (e.g., prosthesis control). In most cases, sEMG signals are sampled, amplified, denoised, and segmented, then, features are extracted as inputs to a classifier. Some sEMG features in time and frequency domains are summarized in [4], among them, features such as mean absolute value and root mean square (RMS) are extensively used because of their computational simplicity and high classification performance in general.

Gibert *et al.* [5] employ eight channel bipolar facial sEMG to discriminate the facial expressions of six basic emotions from a test subject. The feature for classification is the envelope values derived from the absolute value of sEMG signal. Six Gaussian models are built for each expression and are tested for 92% average recognition rate. The sEMG data is collected by using commercial devices and software. They conclude that this system will be capable of delivering real-time recognition response, if simple and light-weight computations (without segmentation) are employed. However, because of using unsegmented data as an input to the classifier, there is too much jitter in classification outputs. Broek *et al.* [6] use three channel biopolar facial sEMG plus electrodermal activity to classify four emotion states: neutral, positive, negative and mixed. Data is recorded from 21 people and the classification reaches an upper correctness of 61.31% among several classifiers including k-nearest neighbors, support vector machines and artificial neural networks with features of mean, absolute deviation, standard deviation, variance, skewness, and kurtosis.

Regarding remote real-time sEMG data monitoring, Attenberger *et al.* [7] present a setup for transmission and visualization of sEMG data on a tablet PC. They utilize a commercial EMG system for gathering one channel sEMG data at 1kHz from forearm. Then the data is transmitted using an Aruidno Uno board with an Ethernet shield to an iPad via an access point. Finally, sEMG data and the corresponding extracted features are visualized on a specific iPad application. In this system, raw and processed sEMG signal can be monitored remotely, however wireless communication is not provided and the device is not portable. Moreover, they applied threshold based approach to recognise two hand gestures where it can be better classified and recognised if classification based approaches are adopted.

TABLE I
PAIN RELATED FACIAL MUSCLES AND FACIAL ACTION UNITS

Facial muscle	Facial Action Units
Corrugator	Brow lower
Orbicularis oculi	Lids tighten Cheek raise Eyes closed
Levator	Nose wrinkle Upper lip raiser Eyes closed
Zygomaticus	Lip corner pull

With the aim of providing a wireless system for healthcare environments, Kobayashi introduces a universal interface which together with electrodes and a wireless module is used for collecting bio-signals (e.g., ECG, EMG) and transmitting the signals to a computer via ZigBee protocol [8]. Even though the approach is efficient in terms of cost and real-time response, it can handle only a single EMG channel as the maximum bandwidth is about 22kbps. Another approach called VAMPIRE-BAT is also based on Zigbee protocol for transmitting EMG data [9]. The system provides several benefits such as low cost, small, and light-weight implementation, and on-line parameter adjustment. However, the system only supports up to 22kbps per channel and it handle a single EMG channel in maximum. The aforementioned ZigBee-based systems are targeted and designed for data acquisition and wireless transmission for a miniaturized single device, and they do not focus on on-line signal processing and data analysis. It should be also mentioned that in the Internet-of-Things era, devices are supposed to be connected (often in a 24/7 fashion) to Internet in a way that the extension of the conventional Internet is realized. This necessitates to follow Internet Protocol (IP) and be compatible with the IP-based networks. That is the reason why either IP based protocols such as 6LoWPAN or Wi-Fi is preferred, or protocol conversion from non-IP-based protocols (e.g., ZigBee) to IP-based protocols is needed at gateways. This is another factor which differentiates the aforementioned ZigBee-based systems with our IoT-based platform.

III. sEMG SIGNAL AQUISITION, PROCESSING AND PATTERN TRAINING

As a part of work for facial expression recognition, pain expressions are chosen for a case study and four pain expressions related facial muscles are the sEMG inputs. The names of muscles and the facial action units they dominate in adults are listed in Table I. Electrodes are reduced in number by utilizing unipolar configuration in amplifier to mitigate their obtrusiveness on face. To capture facial muscle activities, pre-gelled Ag/AgCl sensors are placed on four muscles on the

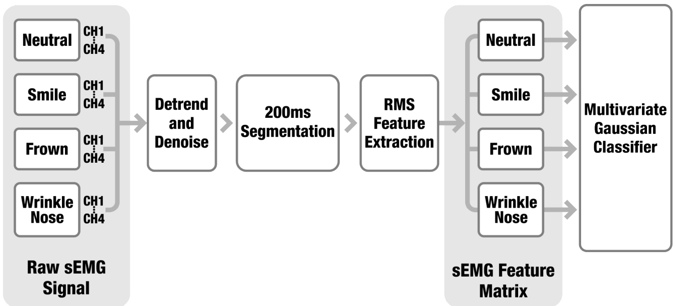

Fig. 1. sEMG signal processing and pattern training flow chart

left side of a face according to the human electromyographic guidelines [10]. The common reference electrode is placed on the bony area behind the left ear. Facial sEMG signals are gathered when the person is with a neutral expression and three facial expressions: smile, frown and wrinkle nose.

The steps to process sEMG data for training a classifier are shown in Figure 1. sEMG signals are sampled from the four channels at 1000 SPS. After the sampling, a 20Hz highpass Butterworth filter and a 50Hz notch Butterworth filter are applied to each signal to diminish the influence of artifacts and power line interference coupled to lead wire. Before RMS feature extraction and constructing a feature matrix, the data is segmented into 200ms slices. The RMS features are extracted using the following formula:

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

A multivariate classifier is trained for expression classification. Parameters of Gaussian distribution for each expression are estimated from training data, i.e. the feature matrix. Then the posterior probability of a given class c in the test data is calculated for pattern recognition [11]. The equation below is Bayes theorem for the univariate Gaussian, where the probability density function of continuous random variable x given class c is represented as a Gaussian with mean μ_c and variance σ_c^2.

$$P(c|x) \propto \frac{1}{2\pi\sigma_c}\exp\left(\frac{-(x-\mu_c)^2}{2\sigma_c^2}\right)P(c)$$

IV. System Architecture

The architecture of the proposed system is presented in Figure 2. The system enables remote monitoring of biopotentials using a multi-channel biopotential measurement device. The device is battery powered and transmits data to Cloud wirelessly via the e-Health gateway. In Cloud, data is processed and classified after which it can be shown to an end user using a webpage or a dedicated Cloud-based application.

A. Data Gathering

Biopotential is a voltage produced by a tissue of the body, particularly muscle tissue during a contraction [12]. For example, ECG depends on measurement of changing potential in contracting heart muscle and it is for heart activity monitoring. Similarly, EMG and EEG are applied in the examination of neuromuscular and brain activities, separately. Besides being applied in clinical monitoring and diagnosis, biopotentials are also widely applied in emerging human-computer interaction when human beings' hand gestures, affective states or brain activity pattern are read and understood by a machine.

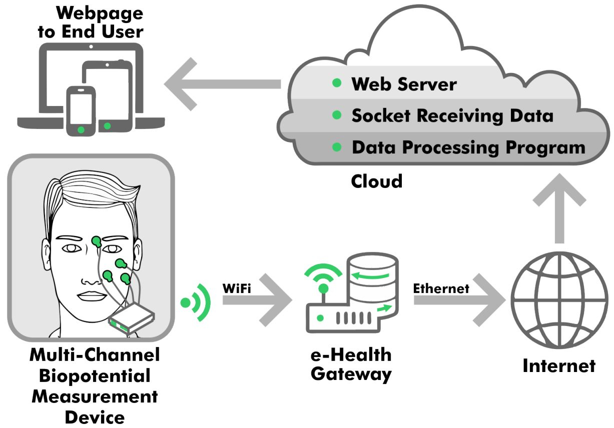

Fig. 2. Data transmission flow in the system

Although biopotentials are applied in different scenarios, most of them need multiple channels of biopotentials as the system input. To recognise facial expressions with sEMG method, three to eight channels of sEMG signals are needed. The requirement of the amount of electrodes varies in ECG monitoring, which depends on ECG leads. There are 1-lead, 3-lead and 12-lead ECG and they need two electrodes, three electrodes and ten electrodes, respectively [13]. While EEG applications need the largest number of channel which can be as large as 35 or even more [14]. The sample rate of each biopotential channel when being digitalized is usually at least 250 SPS. For sEMG signal, the sample rate less than 1000 SPS may irreparably distort the signal due to aliasing [15].

B. Data Transmission

Data transmission plays an essential role in IoT-based applications in various fields. In healthcare applications, data including environmental and bio-data is collected by sensor nodes. This data, which can be raw data without any processing, is transmitted via one or several wireless communication protocols to a Cloud server through a wireless access gateway. Then, the data can be accessed by end users such as medical doctors or caregivers via a mobile application or a browser [16]. As mentioned, data transmission in healthcare applications is carried our via a multitude of devices. Accordingly, a possibility of invalid data during transmitting in the might be elevated. The invalid data, which can be mismatch data caused by network's high latency, may cause serious impacts on disease analysis and treatments. Therefore, with the view of ascertaining data validity in terms of network's latency, a standard for e-heatlh data shown in Table II defined by IEEE 1073 (e.g. X73) [17, 18] is considered as a vital requirement.

TABLE II
REQUIREMENTS OF VARIOUS E-HEALTH SIGNALS DATA RATE AND LATENCY

Bio-medical Signal	Data Rate	Latency
Heart Rate	80-800bps	<1s
Blood Pressure	80-800bps	<1s
Respiration	50-120bps	<300ms
Accelerometer	<100bps	<300ms
ECG	4kbps per channel	<250ms per channel
EMG	64 kbps per channel	<15.6ms per channel
EEG	3kbps per channel s	<350ms per channel

TABLE III
CHARACTERISTICS OF POPULAR WIRELESS COMMUNICATION PROTOCOLS

Protocol	6LoWPAN/Zigbee	Wi-Fi (IEEE 802.11)	Bluetooth Low Energy
Radio Frequency	2.4GHz	2.4GHz	2.4GHz
Bandwidth	250Kbps	100Mbps	1Mbps
Range (meters)	1-75	1-100 (typical)	1-100 (typical)
Topology	Star, Mesh, Tree	Tree	Tree
Peak Current	<15mA	<300mA	<15mA
Standby Current	0.003mA	20mA	0.2mA

The standard includes requirements of vital e-health signals such as heart rate, blood pressure, respiration, ECG, EMG, and EEG. In this paper, with the intention of providing a real-time EMG monitoring IoT-based system, those strict requirements of e-health data are fulfilled. As mentioned, e-health data in health monitoring IoT-based system cannot reach to end-users without an assistance of a wireless communication protocol such as Bluetooth Low Energy (BLE), Zigbee, Wi-Fi or IPv6 over Low power Wireless Personal Area Networks (6LoWPAN) [19]. Each wireless protocol has particular characteristics regarding to radio frequency, communication distance, power consumption, and bandwidth as shown in Table III [18, 20, 21]. For example, some protocols including BLE and 6LoWPAN have a short communication range, low transmission data rate but consume low power for data transmission whilst some others such as Wi-Fi are utterly opposite. Depending on a specific health monitoring application, a particular wireless communication protocol should be effectively utilized. For example, an application for monitoring athlete's heart rate and posture does not require high transmission data rate due to requirements and characteristics of heart rate and accelerometer data. In meanwhile, the application must have a capability of operating during a long period of time with low energy consumption. Therefore, BLE should be the most suitable candidate for this application. In contrast, the proposed system's main target is to monitor 8 EMG channel signals which must be acquired and transmitted with high data rate around 24KB/s per channel for achieving a high signal quality. In addition, in a view of providing a system which can support a multitude of wireless sensor nodes simultaneously, there is a need of a wireless protocol offering high bandwidth transmission. For these reasons, Wi-Fi is considered as the most suitable protocol for our approach as well as other EMG monitoring applications.

C. Data Processing and Result Visualization

For most of raw biopotential data, contaminated by the environment noise or human body movement are inevitable. One common contamination source among biopotential signals is power line interference, composed with 50Hz or 60Hz and its harmonics. Another common noise source in ECG and EMG is body movement that dominates low frequency part of the signal. There are some other noise sources in EMG and EEG. For example, EMG from limb muscles can be contaminated by ECG signal and similarly, EEG can be contaminated by EMG and ECG and ocular artifacts. Therefore, denoising is the basic processing applied in biopotential signals. A variety of filters from FIR or IIR, adaptive ones, to wavelet method can be applied in terms of noise cancellation in order to improve signal to noise rate. In addition to displaying biopotential signals, many applications combine machine learning with biopotential signal processing to achieve automated diagnosis system or pattern recognition system. The signal processing procedures are similar with the ones shown in Figure 1, where feature or features are extracted from the segmented signals for training or testing a classifier.

In a IoT-based system shown in Figure 2, there are several options for implementing signal processing, in one part or several parts separately from the embedded processor in the biopotential measurement device, to a potential smart gateway [22], to the Cloud. Although for supervised or unsupervised learning, training is pre-established off-line, current machine learning algorithms require less constrained computation resources, which makes the Cloud as a proper candidate to implement part or all of the signal processing and data analysis. The data processing and analysis program can receive streaming data by opening the User Datagram Protocol (UDP) socket based on the port or service name.

V. IMPLEMENTATION AND RESULTS

When employing multivariate Gaussian classifier, as introduced in Section III, 10 fold cross-validation is applied and the classification accuracy is 82.4%. The scatter plot of the RMS features of four expressions from one fold training dataset with three of the four channels sEMG are shown in Figure 3. Each test dataset is combined by four expressions in the sequence of neutral, smile, frown and wrinkle nose. Figure 4 presents the classification result from one test dataset. The number on the y-axis in Figure 4 indicates the classification result. From one to four, the number represents neutral, smile, frown and wrinkle nose, respectively. It shows that there is a classification error at the 41st data point where the frown expression is misclassified as the neutral expression.

The prototype of the system is implemented as the block diagram presents in Figure 5. There are five main parts cooperating in it, they are multi-channel biopotential measurement device with Wi-Fi data transmission, gateway, LabVIEW in Cloud, Node.js server in Cloud and webpage for end

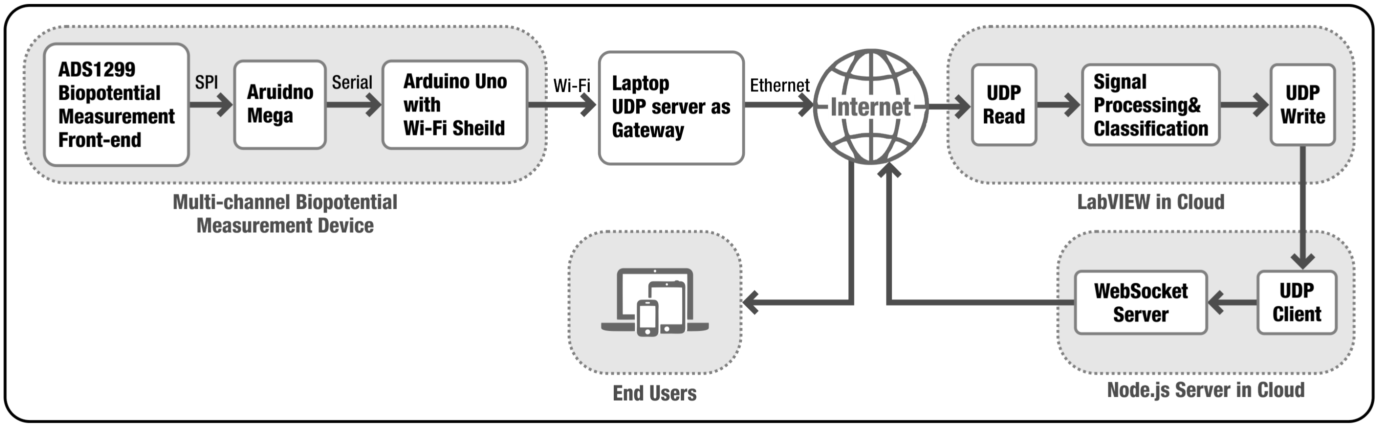

Fig. 5. System implementation block diagram

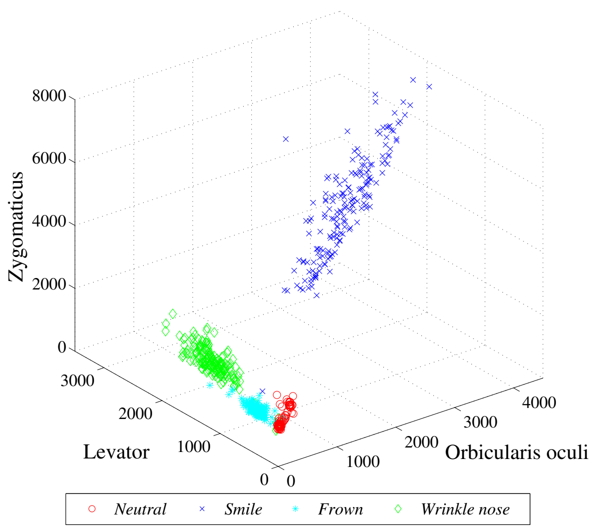

Fig. 3. RMS feature of training data from four expressions

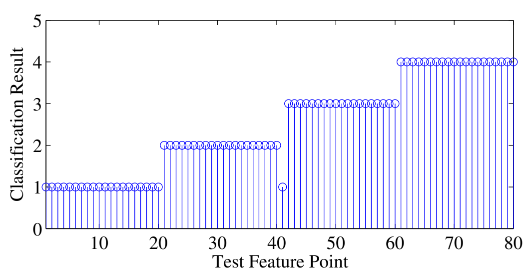

Fig. 4. Classification result

users. In the prototype, ADS1299EEG-FE EVM daughter card from Texas Instruments is used as the sEMG data gathering device. The core of it is an 8-channel, 24-bit analog front end for biopotential measurements. The sample rate of each channel can be set between 250 SPS and 16 kSPS. Arduino microcontroller is used to configure ADS1299 and read data continuously through serial peripheral interface. Arduino Wi-Fi shield, together with Aruidno Uno is utilized for transferring data wirelessly to the access point. A laptop connected to the Internet with Ethernet cable works as the Wi-Fi access point and a desktop connected to Internet works as a Cloud server. In the Cloud, data receiving and processing features are built in LabVIEW virtual instrument where there are built-in UDP and TCP/IP communication functions, together with signal processing functions including several types of filters and installable toolkit such as machine learning toolkit and biomedical toolkit [23, 24]. The web socket runs as one part of the node.js server, which is lightweight and can handle a large number of simultaneous requests. It takes the processed data from LabVIEW also through UDP protocol.

Figure 6 shows the front panel of the LabVIEW virtual machine where sEMG data stream is processed and updated every one second. Butterworth notch and highpass filters are applied in every one thousand samples each channel. Applying filters causes signal distortion with amplitude shooting up in the front of every signal segment, so the RMS feature extracted only from the last 600 filtered samples is classified. The presented signals are filtered sEMG signals from a smile expression. Trained multivariate Gaussian classifier with mean and covariance parameters is embedded in the virtual instrument as MATLAB script nodes. Figure 7 illustrates the web page for remote data visualization, which can display the downsampled processed data stream and the classified expression result. The data and information is updated every one second.

VI. Conclusion and Future Work

In this paper, we implemented a IoT-based remote multi-channel biopotential monitoring system with supervised machine learning. The biopotential measurement device is portable with wireless data stream transmission. Four channel biopotential measurements are taken according to the application requirement. However, current system can support wireless data transmitting and on-line processing for the full eight channels with bytes transmitting at a data rate of 24KB/s. The system can also work for other multi-channel biopotential

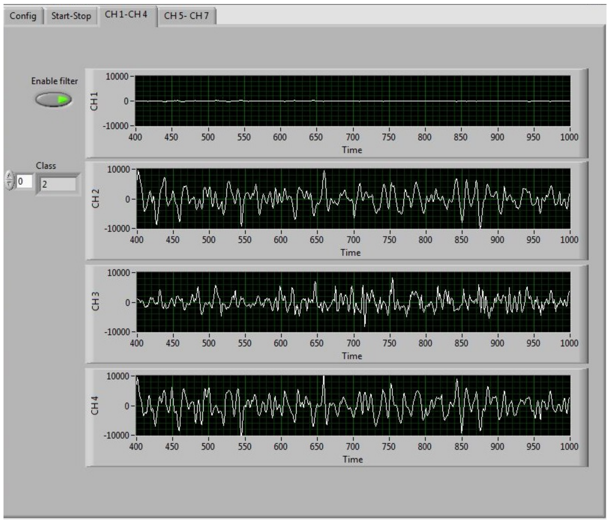

Fig. 6. EMG data stream processing and classification in LabVIEW

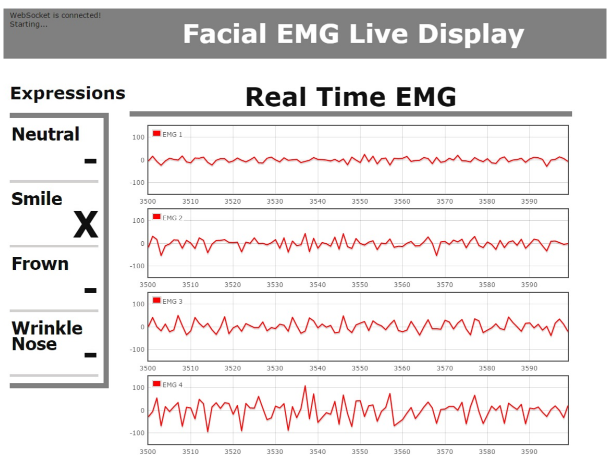

Fig. 7. Web page for remote sEMG data visualization

applications where needs remote monitoring and on-line data analysis such as multi-lead ECG analysis and EEG pattern analysis. The future work can be expanded from several aspects on implementation such as integrating electrodes, lead wires, multi-channel biopotential measurement front end, microcontroller, Wi-Fi module and battery into one wearable device in small size and extending the system for facial expression remote monitoring serving multiple users. At the same time, other classifier options as well as algorithms regarding signals processing can be added to the system, for example, applying wavelet analysis and Hilbert-Huang transform in biopotential signal processing.

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