A Data Acquisiton System with sEMG Signal and Camera Images for Finger Classification with Machine Learning Algorithms

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ABSTRACT

Advances in robotics and biomedical engineering have expanded the possibilities of Human-Computer Interaction (HCI) in the last few years. The identification of hand movements is the accurate and real-time signal acquisition of hand movements through the use of image-based systems and surface electromyography sensors. This study uses multithreading to record motion signals from the forearm muscles in conjunction with a surface electromyography (sEMG) sensor and a camera image. The finger movement information labels were tabulated and analyzed along with the simultaneous acquisition of surface electromyography signals and these gestures through the camera. After the acquisition, signal processing techniques were applied to the sEMG signal markered from the camera. Therefore, once the interface is established, data sets suitable for machine learning can be generated.

Keywords-sEMG; image processing; real-time data acquisition; signal processing

I. INTRODUCTION

Surface electromyography (sEMG) signals are being explored for robotic control, but their multidimensional nature poses challenges in motion translation. Integrating sEMG signals with camera-based image signals is a promising approach. Robotic arms play a critical role in the integration of artificial intelligence. They are in high demand and have drawn numerous research investigations from both academia and business [1]. sEMG is a non-invasively technique, recording data from the skin's surface, and is thought to be a useful source for Human-Computer Interaction (HCI), which offers a natural manner of control. It represents a person's neuromuscular activity and neurological information [2]. Authors in [3] developed a sEMG signal acquisition instrument for body rehabilitation training. They used the ADS1294 chip and STM32 master hardware circuit to achieve the sEMG signal acquisition; then the acquisition software was to read and send the sEMG signal data. Authors in [4] reached a consensus on the acceptance of using a universal user interface model. The users' attitude towards the suggested application was reported as effective, pleasant, and enjoyable. They measured ease of use, consistency, operability, perceived usefulness, minimal memory load, system usability scale, understandability, and learnability through a survey questionnaire. The results illustrate that their proposed solution is more robust, easy to use, and adaptable than other solutions operated through accessibility services [4]. Regarding real-time data acquisition, authors in [5] presented an automated weather station for real-time and local measurements based on an embedded system that continuously measures several weather factors.

II. MATERIALS AND METHODS

Nine healthy participants, with a mean age of 41.3 ± 12.0 years (two females and seven males), volunteered to take part in this study. Using the right hand, the subjects' sEMG signals and the camera-derived finger movement states of six positions (Tumb, Index, Middle, Ring, Pinky, and Open, which is the relaxed position of the fingers without movement) were simultaneously recorded in real time. None of the participants had a prior history of neuromuscular disease, and all were thoroughly informed about the experimental protocol prior to their participation.

A. *Integrated Method: Combining Camera and sEMG Data*

The current study proposes a novel way of HCI using forearm sEMG) biosignal data and camera image processing data. There are several steps in the process, which are depicted in the block diagram of Figure 1.

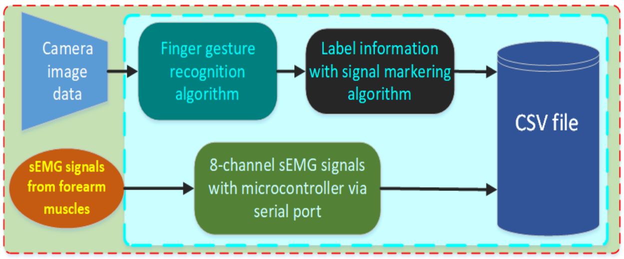

Fig. 1. Real-time hybrid data acquisiton HCI for sEMG signals and camera images.

A finger identification algorithm records hand movement data acquired from the camera in order to identify hand movements. This was made possible by the Python-programmed HCI implementation shown in Figure 2. Thirty five seconds were recorded during the real-time sEMG and camera data collection. To precisely capture muscle action using the sEMG signal, an image processing package was used. In order for their movements to be classified, volunteers had to follow the instructions displayed on the screen for each movement (3 seconds on, 3 seconds off, 5 repeats). Multichannel wearable technologies, such the Myo Armband, greatly improve the recognition of numerous hand gestures from EMG data obtained using multichannel devices, providing several advantages over single-channel devices in biomedical applications [6].

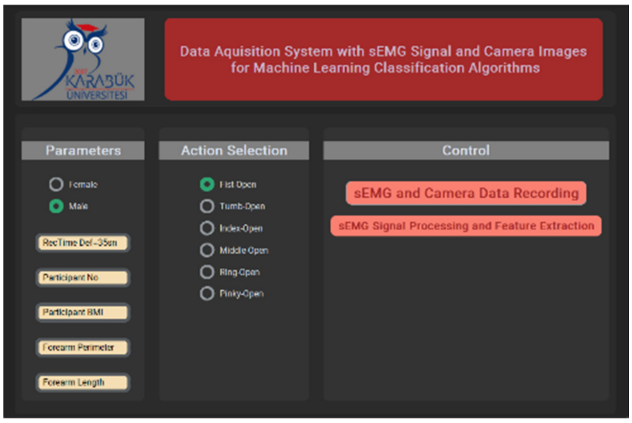

Fig. 2. sEMG-HCI data recording interface and finger identification algorithm.

Biosignal data were collected from every channel at a sampling frequency of 240 Hz. As shown in Figure 3, a microcontroller with a 16-bit ADC input was then used to transport the data to the computer environment via a serial port. A forearm band featuring dry surface electrodes was created in order to gather sEMG data from the forearm muscles. Eight sEMG amplifier circuits were linked to the electrodes by a 3.5" TTS cable, and a microcontroller with eight 16-bit ADC inputs was attached to the amplifier circuit's signal outputs. The USB cable of the microcontroller, which was connected to the data recording interface made in the computer environment for 8-channel sEMG recording, had the DC power line and the data line separated by a USB isolator in order to guarantee the accuracy of the data.

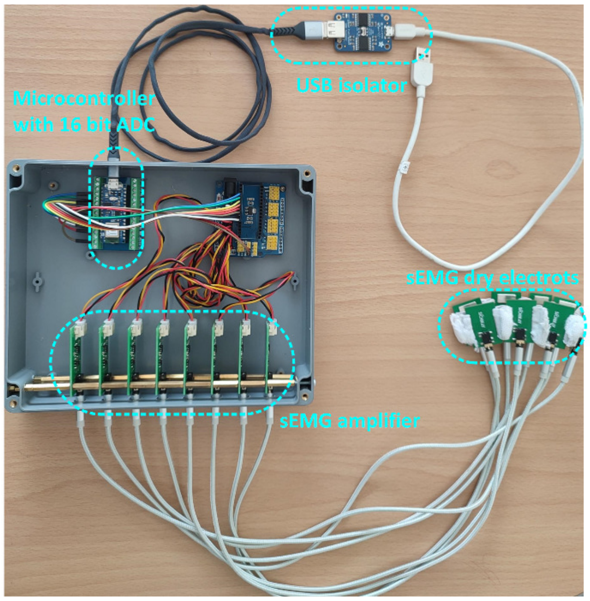

Fig. 3. Real-time hybrid data acquisiton HCI for sEMG signals and camera images prototype.

The 8 sEMG sensor electrodes were placed on the cross-section of the forearm as sensors 5 and 4 [7] were replaced with sEMG-0 and sEMG-1, respectively, and the others were replaced in this order. The remaining sensors were put together into a ring and were assigned numbers. The study employed dry electrodes, and the (+), (-), and reference points were positioned side by side to form one electrode, obviating the need for a separate reference electrode.

B. Image Processing and Camera Image Data for Finger Detection

The camera picture data were generated by the MediaPipe (Hand Tracking) library, which uses digital image processing to identify finger joint points. Within the identified hand regions, the library is able to locate the crucial point of the 21 hand-joint coordinates [8]. With the MediaPipe library, the finger identification algorithm was developed as shown in Figure 4.

The hand was in an open position and was marked as "Open" if the number of fingers with function was equal to five. In order to label the sEMG signal for no movement in real-time, the markering subroutine has been invoked using the algorithm in the red-lined area. If the counted finger number was equal to 0 instead of 5, it meant that all fingers were closed and this gesture was marked as "Fist." To mark the sEMG signal for hand movement, the markering subroutine has been called. One finger had to be closed in order to have the smallest distance possible from the distance measurement if the counted fingers were equal to 4. To calculate the distance between each fingertip and the wrist point (0) in Figure 5, we used the Euclidean distance formula:

$$dst = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (1)$$

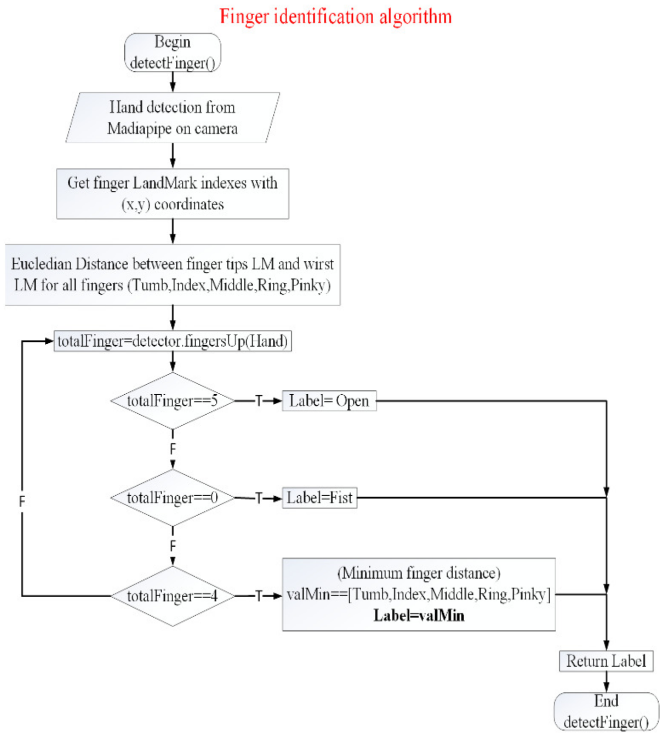

Fig. 4. Finger identification algorithm.

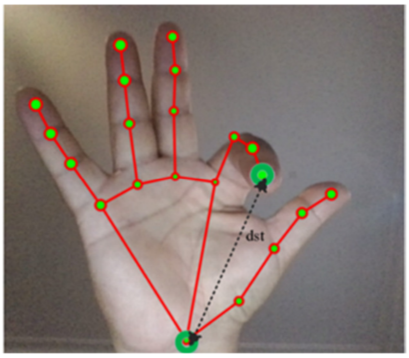

Fig. 5. The changeable distance between the terminal point (8) of the index finger and the wrist point (0).

Fig. 6. Finger identification algorithm on recording.

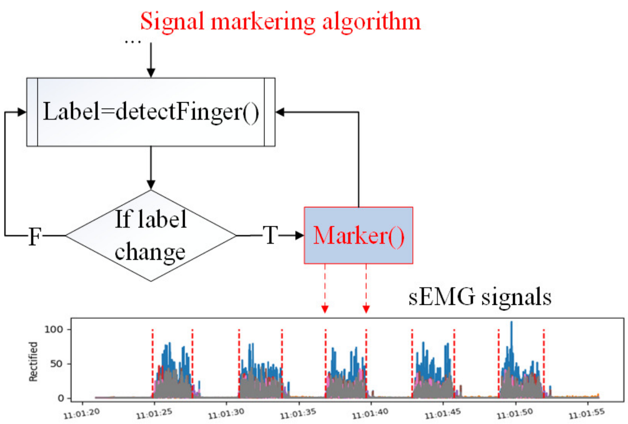

Fig. 7. Signal markering subroutine.

To provide a regulated recording process for the participants, finger identifications were shown on the screen during the recording of sEMG signals (Figure 6). The interface screen featured finger motion data validated by the created algorithm in the left corner, a time counter in the center, and on-off motion commands in the right corner. This made it possible to record the same moment every time and to capture each movement more than once. The stages of picture processing were carried out at a speed of 15 fps.

As can be observed in Figure 7, the sEMG signal was registered on finger movement timings when the label changed in the signal markering subroutine. It indicated if volunteers closed all or just one finger. Their hand was considered open if they did not close any fingers. Because of the camera-based image processing, the start and end points of the sEMG signal were marked, and a valid dataset was constructed.

C. sEMG Signal Processing and Feature Extraction

In the current study, the sEMG signal was first subjected to a band-pass filter to extract features. The filtered signal was then rectified and subjected to smoothing and overlapping windowing techniques [9]. A feature extraction function was developed by selecting a period of 150 ms and a processing time of 25 ms [10]. It can be difficult to distinguish between signals from different muscles and noise when interpreting EMG signals for limb motions. Using popular feature types like RMS, VAR, MAV, IEMG, WL, MNP, TP, and MNF, a high-performing EMG classification system was created to solve this problem [11]. These characteristics were chosen because they are common in earlier research.

Root Mean Square (RMS): RMS is a feature used in EMG analysis. Equation (2) illustrates how it relates to non-fatiguing contraction and constant force [12].

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

Variance (VAR) is generally defined as the average of square values of the variable's deviation. However, the EMG signal's mean value is very near to zero (~10–10) [13].

$$\mathrm{VAR} = \frac{1}{N-1}\Sigma_{\mathrm{i=1}}^{N}(x_i - \bar{x})^2 \tag{3}$$

In clinical practice, integrated electromyography (iEMG) is a measurement that is frequently used to identify patterns of muscle activity without depending on EMG data using (4). In patient assessments, it is frequently utilized as an initial detection index [14].

$$\mathrm{iEMG} = \sum_{i=1}^{N}|x_i| \tag{4}$$

In MAV, $|x_i|$ is the magnitude of the i^{th} sample of x and N represents the total number of samples in a segment [15]:

$$\mathrm{MAV} = \frac{1}{N}\Sigma_{\mathrm{i=1}}^{N}|x_i| \tag{5}$$

WL is defined as the wavelength of an EMG signal over a segment [16]:

$$\mathrm{WL} = \sum_{i=2}^{N}|x_i - x_{i-1}| \tag{6}$$

Furthermore, using (7)-(9), the frequency domain characteristics MNP, TP, and MNF are computed [17-19]:

$$\mathrm{MNP} = \frac{1}{N}\Sigma_{\mathrm{i=1}}^{N} x_i^2 \tag{7}$$

$$\mathrm{TP} = \sum_{i=1}^{N} X(f_i)^2 \tag{8}$$

$$\mathrm{MNF} = \frac{\sum_{i=1}^{N} f_i \cdot X(f_i)^2}{\sum_{i=1}^{N} X(f_i)^2} \tag{9}$$

As a result of applying signal processing techniques to the sEMG signal, the signals shown in Figure 8 were created.

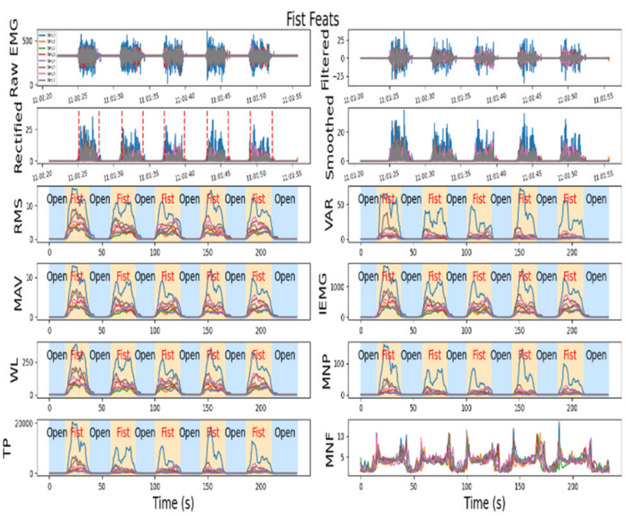

Fig. 8. The results of applying signal processing techniques to the 8-channel sEMG signal.

With this study, 8-channel sEMG signal data can be recorded in real-time with the help of the finger identification algorithm on the created interface. With this approach, the process of recording muscle data with the sEMG sensor while users make finger movements can be done with visual guidance. With the recording data being more controlled, a functional interface has been developed to create the necessary data set for machine learning as a result of signal processing techniques.

III. CONCLUSION

The finger movement detection method in this system was created using image processing and multithreading. It comes with an armband that can record 8-channel sEMG data. In contrast to the sEMG hybrid data collection and classification research, the purpose of the current study was to assess the efficacy of a real-time hybrid data acquisition system. Table I presents a comparison of the developed system with related studies. Image data source, sEMG data source, and features are detailed in Table I. In this study, the sEMG signals and image data sources were used in real-time, which facilitated the comparison of data.

TABLE I. COMPARISON OF THE DEVELOPED SYSTEM WITH RELEATED STUDIES

Work	Image source	sEMG source	Features
[20]	LeapMotion	4-channel sEMG data aquisition system	MAV, ZC, Slope sign change, DAMV, VAR, joint angle, finger wrist distance
[21]	Dynamic Vision Sensor (DVS)	MyoArmband (8-channel sEMG band) 200 Hz	MAV, RMS
[22]	LeapMotion	MyoArmband (8-channel sEMG band) 200 Hz	RMS + LeapMotion features + feature fusion
[23]	Motion capture system with 12 cameras	Delsys's TrignoTM Wireless EMG System	RMS
[24]	Azure Kinect + Google Mediapipe	-	Movement area average, Coefficient of Variation
Proposed	PC Camera + Google Mediapipe	8-channel sEMG armband design 240 Hz	RMS, VAR, MAV, IEMG, WL, MNP, TP, MNF
	Real-Time data aquisition		

Promising outcomes have been found in the study of the 8-channel sEMG signal and its real-time motion estimatation by image processing methods. The integration of sEMG signals with the MediaPipe library and finger gesture identification algorithm has demonstrated greater effectiveness in real-time acquisition, particularly when visual input sources are utilized. Thus, the real-time data collection interface design required to classify finger movements with machine learning algorithms could be realized with a new method.

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The authors have no conflicts of interest to disclose.

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