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Wearable electromyogram design for finger movements based human-machine interfaces

Parmak hareketlerine dayalı insan-makine arayüzlerine yönelik giyilebilir elektromiyogram tasarımı

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Wearable Electromyogram Design for Finger Movements Based Human-Machine Interfaces

Highlights

- *Wearable electromyography system design*
- *Design of an embedded system to decode finger movements in real time*
- *In offline tests, 99.47% and 98.2% accuracy by using RF and SVM, respectively.*
- *Decoding five finger movements with an accuracy of 92.16% by using MAV and RF in online tests.*
- *Real-time decoding of finger movements in the embedded system in 90ms*
- *Wireless communication with machine interfaces*

Graphical Abstract

In this study, a three-channel wearable EMG amplifier was designed. The EMG signals were used to decode the finger movements by using machine learning algorithms.

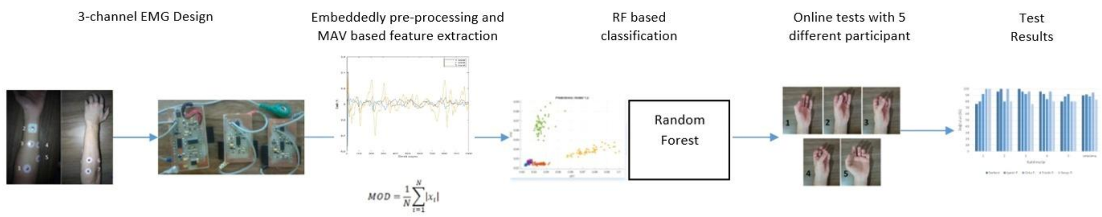

Figure. Block diagram of the wearable electromyogram design for finger movements based human-machine interfaces

Aim

This study aims to design a wearable EMG system that can be used in human-machine interfaces and develop an algorithm for real-time analyze of finger movements.

Design & Methodology

In this study, a three-channel wearable EMG amplifier was designed. The recorded EMG signals were analyzed in real-time, by the algorithm embedded in the ESP8266 based microprocessor. Mean absolute value (MAV) and random forests (RF) were employed for feature extraction and classification, respectively. The determined finger movements were transmitted to the devices wirelessly.

Originality

The wearable EMG system designed in this study can determine five finger movements by using a single feature (MAV) with 92.16% accuracy, in 90 msec, using only three-channel EMG signals and can transmit the determined movements to clients in real-time.

Findings

The designed system was tested on five volunteers. In offline tests, 99.47% and 98.2% accuracies were achieved using RF and SVM respectively. In the online tests, five finger movements were decoded with an accuracy of 92.16% using RF.

Conclusion

The 3-channel wearable EMG system can analyze five finger movements in real-time with 92.16% accuracy in 90 msec by using MAV features and RF algorithm.

Declaration of Ethical Standards

The study was approved by the ethics committee of Gazi University on 23.11.2021 (2021 –18:1051).

Parmak Hareketlerine Dayalı Gerçek Zamanlı İnsan-Makine Arayüzleri için Giyilebilir Elektromiyogram Tasarımı

Araştırma Makalesi / Research Article

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ÖZ

Bu çalışmada, insan-makine arayüzlerinde kullanılmak amacıyla, parmak hareketlerinin çözümlenebilmesine yönelik önkol üzerine giyilebilir bir elektromiyogram (EMG) sistemi tasarlanmıştır. Tasarlanan sistem, kullanıcının hareketlerini kısıtlamadan EMG sinyallerinin ölçümünü yaparak bu ölçümleri sisteme gömülü yazılım aracılığıyla çözümlemekte, oluşturulan cevabı, kontrol edilecek çıkış birimlerine kablosuz iletişim teknikleri ile gerçek zamanlı olarak iletebilmektedir. Çalışmada, üç kanal yapısındaki EMG yükseltecin tasarımı yapılmış ve NodeMCU V3 geliştirme kartının entegre edilebileceği bir sistem gerçekleştirilmiştir. Tasarlanan sistem ile parmak hareketlerine ait öznitelikler mutlak ortalama değer (MOD) kullanılarak elde edilmiş; Destek Vektör Makineleri (DVM) ve Rastgele Orman (RO) yöntemleri kullanılarak sınıflandırılmıştır. Offline testlerde, RO ile %99.47, DVM ile %98.2 doğruluk oranları elde edilmiştir. Offline testlerde %99.47 doğruluk gösteren RO algoritması seçilerek, online testler için gömülü sisteme entegre edilmiştir. Sistem 5 gönüllü ile gerçekleştirilen online testlerde parmak hareketlerini ortalama %92.16 doğrulukla çözümleyebilmiş, sistemin çözümlediği parmak hareketleri ile ilişkilendirilen komutların Kullanıcı Veribloğu İletişim Kuralları (UDP) ağ protokolü ile istemcilere gönderilerek ilgili hareketlerin çıkış birimi arayüzünde görüntülenmesi sağlanmıştır. Sistem 90 ms sürelik bir gecikme ile gerçek zamanlı olarak çalışabilmekte ve tasarlanan çıkış birimi arayüzünde anlık olarak yapılan hareketler görsel olarak görülebilmektedir. Yapılan bu çalışma kas hastalıklarının tespiti, EMG tabanlı giyilebilir protez sistemlerin kontrolü, parmak hareketleri ile kontrol edilebilecek insansız araçların tasarımında önemli bir aşamadır.

Anahtar Kelimeler: Elektromiyogram (EMG), giyilebilir sistemler, insan makine arayüzü, parmak hareketleri.

Wearable Electromyogram Design for Finger Movements Based Real-Time Human-Machine Interfaces

ABSTRACT

In this study, a wearable electromyogram (EMG) system on the forearm was designed to analyze finger movements for use in human-machine interfaces. The designed system measures the EMG signals without restricting the user's movements, analyzes these measurements through the software embedded in the system, and transmits the generated response to the output units to be controlled in real-time with wireless communication techniques. In the study, a three-channel EMG amplifier was designed and a system in which the NodeMCU V3 development board could be integrated was realized.With the system, the features of finger movements were obtained using the Mean Absolute Value (MAV) and classified using Support Vector Machines (SVM) and Random Forest (RF) methods. In offline tests, 99.47% accursacy with RF and 98.2% accuracy with SVM were obtained. The RF algorithm with 99.47% accuracy in offline tests was selected and integrated into the embedded system for online tests. In the online tests performed with five volunteers, the system was able to analyze finger movements with an average accuracy of 92.16%, and the commands associated with the finger movements analyzed by the system were sent to the clients with the User Datagram Protocol (UDP), and the related movements were displayed on the output unit interface. The system can work in real-time with a delay of 90 ms and instantaneous movements can be seen visually on the designed output unit interface. This study is an important step in the detection of muscle diseases, the control of EMG-based wearable prosthetic systems, and the design of unmanned vehicles that can be controlled by finger movements.

Keywords: Electromyogram (EMG), wearable systems, human-machine interfaces, finger movements.

1. INTRODUCTION

Human-Machine Interfaces (HMIs) are systems that allow humans to communicate with machines, systems, or devices. In the traditional HMIs, communication between humans and machine is provided by units such as buttons, switches, and touch screens. Additionally, it has been seen that various devices and applications can be controlled with human-machine interfaces based on control variables such as human voice, eye movements, and head movements [1]. For people who lose voluntary muscle control due to various neuromuscular diseases, such as ALS and SCI, control signals can be obtained

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from human physiological data in HMIs [2]. For this purpose, signals such as electrocardiography (ECG) [3,4], electroencephalogram (EEG) [5,6], electrooculogram (EOG) [7], electromyogram (EMG) [8] can be used as control signals in HMIs.

People make the conscious motor movements they need with skeletal muscles. Skeletal muscles can be controlled by the motor control units to which each fiber is attached. EMGs are devices used to measure and record the electrical activity that occurs because of muscle contraction. In invasive EMG measurements, the amplitudes of the EMG signal range from peak to peak between 0 and 10 mV and the frequency bands vary in the range of 0.1-10 kHz, while in non-invasive applications with surface electrodes, the measurement frequency range decreases to the range of 0.1-500 Hz, depending on the position of the electrodes [9-10]. In addition to having an important place in the diagnosis of various diseases [11], EMG signals can be used in rehabilitation applications [12], control of upper extremity prosthesis [13], and robotic control applications [14]. EMG signals are used in augmented reality applications [15] together with HMIs. In this study, we designed an embedded EMG measurement and recognition system that uses surface EMG (s-EMG) signals as input variables for analyzing the finger gestures by using machine-learning (ML) algorithms in real-time [16, 17].

EMG signals have been used in various studies to analyze the hand and finger movements of both healthy and amputee individuals [18-19,22]. Anfolk et al. [18] designed a 16-channel s-EMG measurement system and determined the 5-finger movements of an amputee with 86% accuracy. In the study by Malešević et al. [19], the 16-channel EMG measurement system was designed and different classification methods were examined with different feature extractions in the classification of s-EMG signals, and an average of 84.30% accuracy was achieved using the Hidden Semi Markov Model algorithm with the mean absolute value (MAV) feature. In the study by Yamaoni et al. [20], a 5-channel EMG measurement system was designed and it was aimed to determine nine different hand movements of an amputee and four different healthy individuals using artificial neural networks (ANN). According to the results of the study, while the average accuracy for the amputee was 30%, the average accuracy was calculated over 80% for healthy individuals. A 3-channel s-EMG measurement system was designed and a wireless vehicle was controlled by taking the amplitude levels of hand movements [21]. By using an 8-channel EMG device, the dataset from nine amputees was classified with LDA, QDA and k-Nearest Neighbors(k-NN) machine learning methods for six different movements, and 82% average accuracy was obtained using k-NN [22]. In the study by Ariyanto et al. [23], 16 features were extracted with a single-channel EMG sensor and five different finger movements were classified with ANN with an accuracy of 96.7%. Caesarendra et al. [24] classified five different finger movements with the 8-channel wearable MYO armband (Thalmic Labs, Waterloo, Canada) using the ANFIS classification method and obtained an accuracy rate of 82%. Since these studies are conducted in laboratory environments, the analysis of signals recorded with EMG devices is done offline on computers. In order for EMG-controlled HMI systems to become widespread, these systems should be designed wearable and embedded work with few electrodes, short processing time and low power consumption.

Wearable technologies are technological systems that can be worn by people and where the data recorded with the sensors can be monitored remotely. Wearable technologies can transfer information from smart sensors to a central unit with wireless communication methods or process data directly. Wearable technologies are developing rapidly with innovations in communication fields such as Wi-Fi systems and the internet, as well as developments in electronic integrated circuit (IC) technology, sensors, and nanotechnology [25].

In order for EMG-controlled HMIs to be used practically in the field of health and industry, it is important to transform these systems into wearable ones. Liu et al. [26] designed a card with a 12-bit resolution, 1.6 kHz sampling frequency, EMG sensors, microprocessor, wireless transmission module and a 4-channel measurement system including the and with this system, using the MAV feature of the signal, it was combined with the ANN classifier. Ten different movements were obtained with an average of 94% accuracy, and these results were transferred wirelessly with the NRF24L01 RF IC. Benatti et al. [27] designed a multilayer printed circuit board with low power consumption and EMG system was designed using an 8-channel Cerebro ASIC analog front-end (AFE) IC with 16-bit resolution, 8 kHz sampling frequency, and STM32F407 microprocessor. With this system, seven different movements were tested with four different people using the support vector machines (SVM) classifier, and it was shown that the system provided an average of 90% accuracy. Zang et al. [16] designed a real-time recognition system for hand gestures with MYO armband and a computer. This system had an average 227.76 ms response time. Chandrasekhar et al. [17] designed a portable, low-cost, 8-channels, real-time s-EMG system. The system was tested with 6-channels and response time was measured as 110 ms. The total cost of the system was about USD 200. The results of the studies in this field indicate that the high number of channels, high processing times, large size, inability to use in real-time and having a wired structure constitute obstacles to the development of wearable EMG systems.

In this study, a wearable EMG system was designed and implemented for real-time analysis of finger movements. The designed 3-channel EMG measurement system enables the measurement of EMG signals over the forearm, and can classify the EMG signals on the embedded system using machine learning methods, and wirelessly transfer the commands related to the determined finger movements to the output units to be controlled through the User Datagram Protocol (UDP). In order to extract the features of the EMG signals, the mean absolute value (MAV) was used. Support Vector Machines (SVM) and Random Forest (RF) algorithms were employed for classification. The performance of the designed system was analyzed by offline analysis of the recorded EMG signals of five participants. Training sets created in offline data analysis were transferred to the embedded system, enabling real-time online operation with the wearable EMG system, and the commands determined by the embedded system were transferred to the output unit wirelessly. With this structure, response time is reduced to 90 ms.

In the second section of the study, the hardware details of the designed wearable EMG system are explained, and the experimental procedures are detailed. In the third section, offline and online test results were given, and results are evaluated in the discussion section. Finally, the results of the study are summarized in the conclusion part.

2. MATERIAL and METHOD

The block diagram of the wearable EMG system designed in the study is shown in Figure 1. Thanks to the surface electrodes, the biopotential signals of the muscles are detected by the EMG amplifier. The signals detected by the EMG amplifier are filtered using band-pass and 50 Hz band-stop analog filters with a cutoff frequency of 10-530 Hz. The obtained signals are amplified with operational amplifiers and read by the NodeMCU V3 [28] development board with the help of ADC (Analog-Digital Converter) IC.

Training sets were created after the feature extraction using the recorded EMG signals, classified using Python with SVM and RF algorithms, and the header file that contains code block translated to C programming language using the micromlgen library [29] was loaded to integrate into the code on the NodeMCU V3 development board. Compile process was conducted with Arduino IDE. Online tests were conducted with five participants using participant-specific training sets. The placements of the electrodes on the forearm, and the device worn by the user are shown in Figure 2.

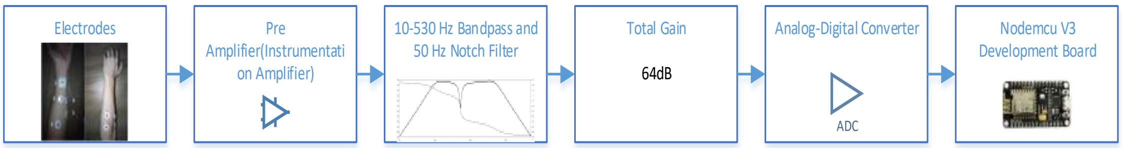
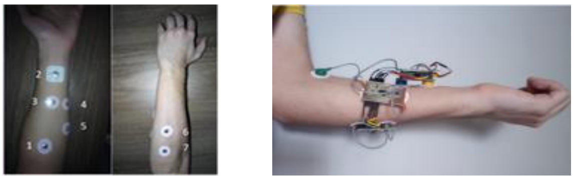


Figure 1. The block diagram of the system



(a) (b)

Figure 2. (a) Position of the electrodes on the forearm, (b) the device on the forearm

The flowchart of the processor is given in Figure 3. According to the flowchart, features are extracted using analog data read by a predetermined sample size; the classifier creates a response by classifying the data using the training set previously embedded in the card, and this answer is shared in real time over the network to which the system is connected by the UDP method. UDP is a network communication protocol that uses the datagram unit of packet-switched computer communication between devices connected to the same network and is referenced to the Internet Protocol (IP) [30].

The movements that are resolved based on the client's query are transmitted with a 90 ms delay from the defined IP and port address of the designed system. The shared answers are displayed on the screen and the query is sent again. In case there is no new response as a result of the query, the interface software shows the fixed hand movement.

2.1 EMG Amplifier Design

In this study, three modules were designed for the EMG system. The modules are shown in Figure 4. Figure 4 (a) includes the EMG amplifier, the socket for the module to be attached to the electrodes, the MCP3204 analog-to-digital converter (ADC) IC, the NodeMCU V3 development board, the negative voltage circuit, the reference voltage circuit and the 440 mAh Li-Polymer battery. Its dimensions are 32x57x20 mm. The two modules seen in Figures 4 (b) and 4 (c) are identical and contain only the EMG amplifier and the necessary socket for attaching the module to the electrodes. Wired connections are established between the modules. Its dimensions are 29x50x8 mm.

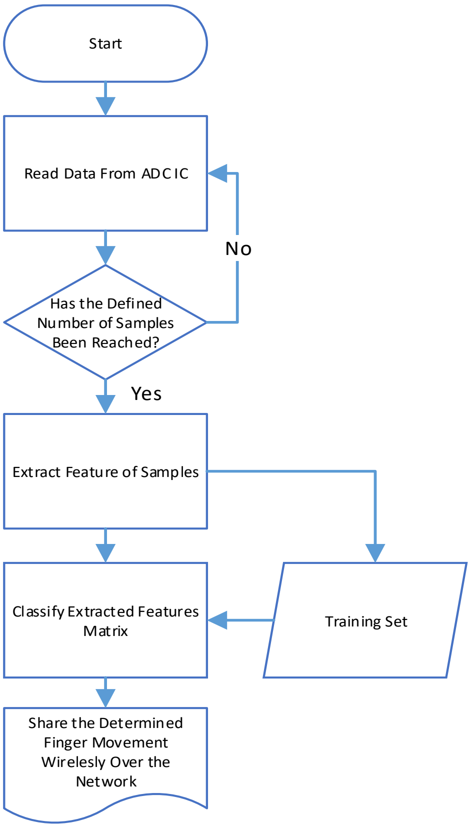


Figure 3. The flowchart of NodeMcu V3 development board

During s-EMG measurement, EMG signals can be affected by electrical noise due to their low amplitude. The main reasons of this are that electrical noise can reach the surface electrodes over the body, and the surface contact of the electrodes is not provided well. In

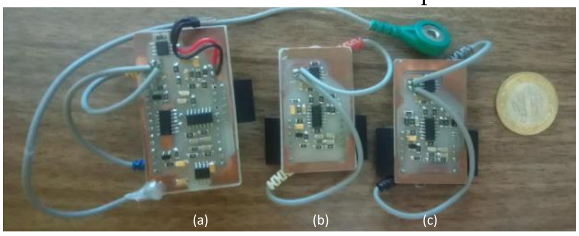


Figure 4. (a) Development board, EMG amplifier, main module containing reference and negative voltage circuits and battery, (b) and (c) Modules that contain EMG amplifiers and can be wired to the main module

order to eliminate interference noises, the common mode rejection ratio (CMRR) was kept as high as possible. Instrumentation Amplifier (IA) needs a negative voltage to detect the negative part of the EMG signals, while the ADC IC needs a reference voltage to process the negative voltages. The required negative voltage and DC reference voltage are provided by the circuits on the first module. ICL7660 IC is used for negative voltage. For the DC reference voltage, a voltage divider circuit is used together with the LMV321IDBVR operational amplifier to obtain a balanced DC reference voltage. The circuit diagram is given in Figure 5.

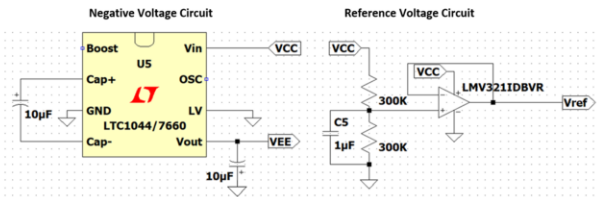


Figure 5. Diagram of negative voltage and DC reference voltage generation circuits

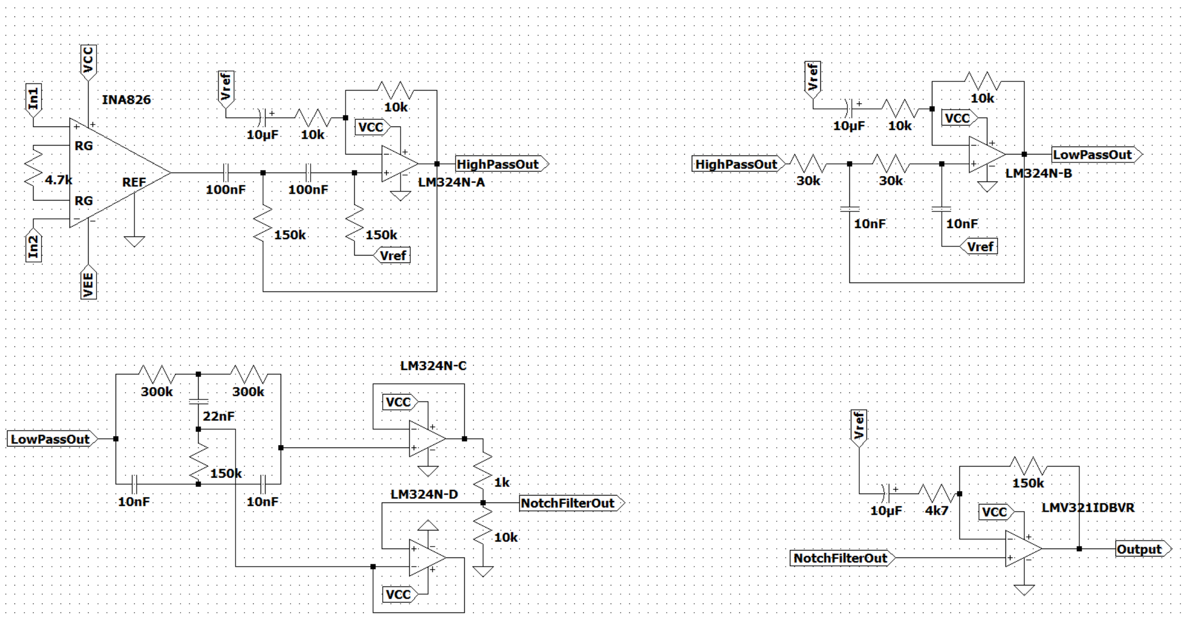


Figure 6. EMG amplifier circuit diagram

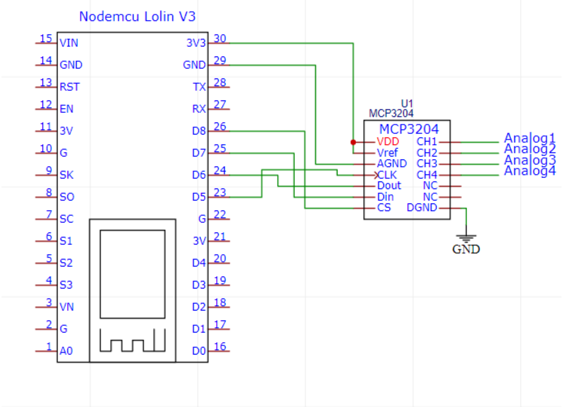


Figure 7. MCP3204 IC and NodeMCU V3 connection

INA826AIDR IA was used in the EMG amplifier. This amplifier, with a gain of approximately 12, provided a CMRR of approximately 110 dB. By adding a DC reference voltage, the data can be read by the ADC. A high-pass filter with a cut-off frequency of 10 Hz, a low-pass filter with a cut-off frequency of 530 Hz and a notch filter with a cut-off frequency of 50 Hz were designed. In the last stage of the circuit, the signal was amplified with an operational amplifier. LM324N and LMV321IDBVR operational amplifiers were employed in analog filters and signal amplifier, respectively. A total gain of 64 dB was achieved. In the study, the MCP3204 IC was fed with 3.3 V and used with a clock frequency of 1.35 MHz. An analog signal cycle time was measured as 40 µs. By removing the measured DC reference voltage value from the EMG data, the raw EMG signal can be read in NodeMCU V3. The schematic of the EMG amplifier is given in Figure 6, and the connection between the MCP3204 and the development board is given in Figure 7. The power consumption was measured as 308 mW. Firmware was compiled in Arduino 1.8.13 IDE.

2.2 Experiment Procedure and Data Records

Five volunteers participated in the experiments. The study was approved by the ethics committee of Gazi University. The participants were informed about the purposes, consent and experimental procedure of the study and all the participants signed the informed consent form. Participants used their left arms during the experiments. In order to create the training set, offline data were recorded. Data recording was made using surface electrodes placed on the forearm. The participants were asked to sit upright and keep their arms straight and repeat the finger movements verbally told them. Finger movements seen in Figure 8 were repeated for 210 ms. This process was carried out in 5 sessions at 5-second intervals.

Online tests were carried out with 25 trials for each movement. In the trials, the movements given in Figure 8 were said to the participants as voice commands and they were asked to wait for 5 seconds between each

Figure 8. Finger movements used for testing in the experiment, resting state 'Rest', index finger movement 'I', middle finger movement 'M', ring finger movement 'R', little finger movement 'L'

command. In the online experiments, the designed output user interface was used. While the participants were performing the finger movements, a query was sent to the system from the output user interface and the current response was taken as a result, and the command for the action was displayed on the output user interface.

2.3 Feature Extraction and Classification

In this study, for feature extraction, mean absolute value (MAV), which is a feature that has been successfully used in EMG signal analysis in the literature, was used [18, 19, 26]. The formula for the feature is given in Equation 1. MAV is obtained by summing the absolute values of the analog data received by the EMG amplifier from the first signal to the N^{th} (number of samples) signal and dividing N. x_i refers the i^{th} raw sample.

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{1}$$

In the classification stage, SVM and RF algorithms were employed. SVM is a supervised machine learning method that creates a hyperplane that separates classes. SVM can work with linearly or non-linearly separable data. [31]. For linear SVM, C is a penalty parameter for each misclassified data point. C parameter of the SVM algorithm was determined for every participant individually. RF algorithm is an ensemble method. RF classifier is a classifier that creates more than one decision tree for classification and makes a classification based on the result of these decision trees [32]. For the RF algorithm, the parameters that indicate the number of trees in the forest and the depth of trees in the forest were used as 100 and 2, respectively. In this study, classification algorithms were developed using the Scikit Learn library. Because of superior performance in offline tests and due to the short processing time, we preferred to use the RF algorithm in online tests. The data recorded in the offline experiments were used to construct the training sets and classifier models. The classifier models are installed into the embedded system for use in online experiments. GUI design, offline tests and trained datasets were compiled in Python 3.9.0 IDLE.

3. EXPERIMENTAL RESULTS

In this study, a three-channel wearable real-time EMG measurement and movement detection system was designed and implemented for the analysis of finger movements. Signals recorded on the forearm using the designed EMG system were used to classify finger movements. EMG signals of a participant recorded over three channels for the little finger movement using the designed EMG system are shown in Figure 9.

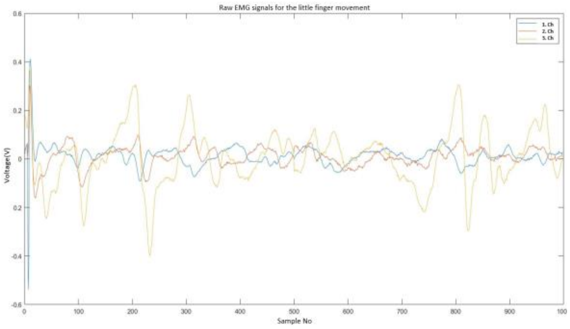


Figure 9. Raw EMG signals for the little finger movement

In the data analysis, EMG signals were first filtered using a band pass filter at a frequency of 10-530 Hz and a 50 Hz notch filter. The filtered EMG signals were decomposed into 20 ms windows with a 10 ms overlapping windowing process. Feature extraction was applied to each time window for the three channels. After the feature extraction process, the feature distributions for each finger movements obtained for the three channels are shown in Figure 10.

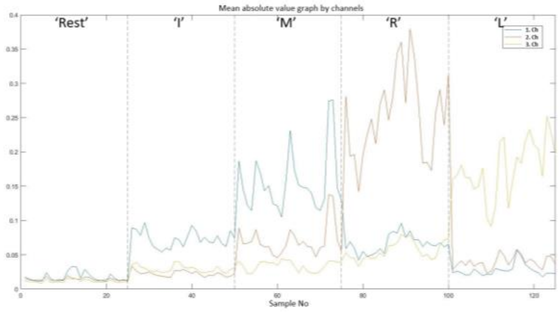


Figure 10. Mean absolute value graph by channels

Firstly, offline data analysis was performed to evaluate the system performance. The SVM and RF algorithms were used in the classification. The classification accuracies obtained by SVM and RF for 5 participants are shown in Figure 11. By using the subject-specific C parameters, finger movement classification accuracy is yielded as 98.2% for SVM in offline tests. The average accuracy rate was 99.47% for RF.

Due to the accuracy rate of the RF algorithm in offline testing, it was decided to use it in embedded system and online tests. The training sets were embedded on NodeMCU V3, and the online operation of the system was ensured. Commands related to finger movements determined by the embedded system were sent to clients wirelessly.

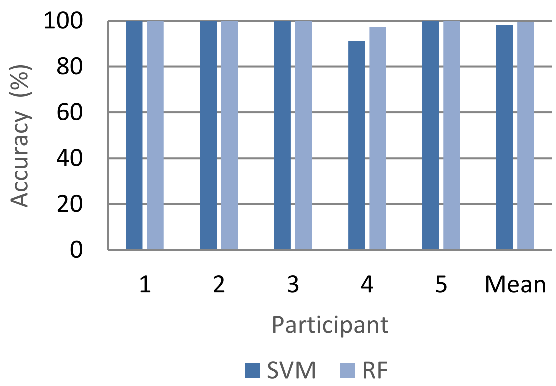


Figure 11. Offline test results

Online experiments were conducted with the same five participants in offline tests. The results of the online tests, which indicate the accuracies of 4 finger movements and resting states are given in Figure 12, and the confusion matrices of the online test results are given in Figure 13. When the online test results are examined, the average accuracy rates are calculated for resting state (b), index (i), middle (o), ring (y) and little (s) fingers as 94.4%, 91.2%, 92.8%, 96% and 86.4%, respectively.

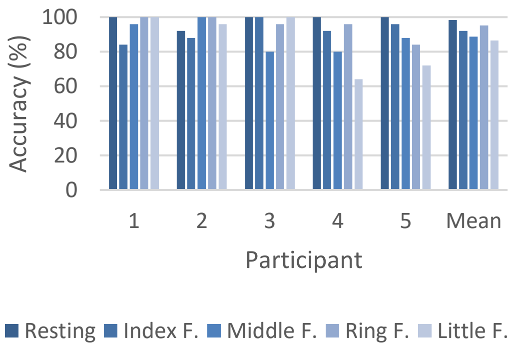


Figure 12. Online test results

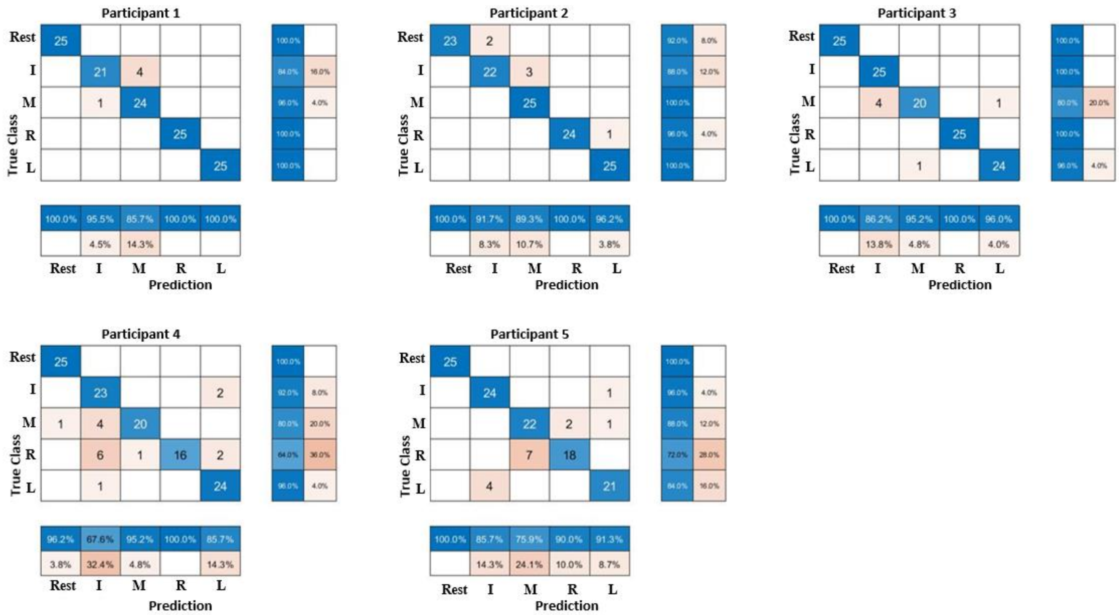
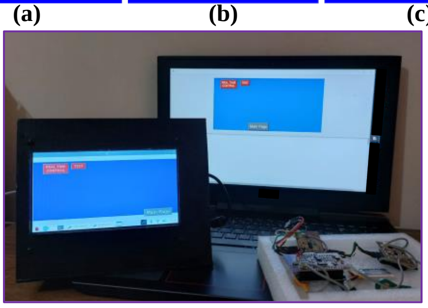


Figure 13. Confusion matrices of online test results

The individual confusion matrices obtained in the online experiments for five participants are shown in Figure 13. Accordingly, since the effects of other finger movements are minimal due to the electrode positions in the ring finger movement, it is thought that the highest accuracy is obtained in this movement. Besides, when the EMG signals during the ring finger movements were examined, it was observed that the signal amplitudes obtained from the second channel electrodes were higher than the other finger movements. It was observed that the little finger movement was classified incorrect during the online tests since the participants also contracted their other fingers during the little finger movement. Therefore, it is thought that the lowest accuracy rate occurs in this finger movement.

Therefore, it is thought that the lowest accuracy rate occurs in this finger movement.

(a) **(b)** **(c)**



(d)

Figure 14. (a) Main page, (b) 'REAL TIME CONTROL' window, (c) 'TEST' window (d) Software on different platforms

The output user interface used during the real-time operation of the study is given in Figure 14 (a-d). The window in which the analyzed movements are displayed in real-time is given in Figure 14 (b), while the window that can display the current movement on the screen when the "Query" button is pressed momentarily is given in Figure 14 (c). In this study, the results obtained were presented as feedback to the user by displaying the image of the movement on the prepared control screen; however, these results can be used to control any system that can operate with discrete commands.

4. DISCUSSIONS

In this study, a wearable EMG system was designed and used to analyze finger movements thanks to its embedded software. The designed system can be used on different muscle groups in the human body to analyze the movements of different limbs. The ultimate purpose of such a system is to contribute to wireless control of EMG-based wearable orthoses or prostheses by analyzing the user's movement intentions, in rehabilitation systems [33]. On the other hand, a wearable EMG system can provide early diagnosis of various muscle diseases by continuous monitoring of patients. While performing different movements, muscle fibers create electrical potentials at different levels and different frequencies for each movement. By analyzing these potentials in the time and frequency domain, it is possible to distinguish between healthy and patient groups [34, 35]. Besides, in unmanned devices, especially for dangerous tasks, wearable controllers can be developed using EMG signals. EMG-based wearable HMIs can be also used to provide control of several output devices by amputee individuals [36].

In EMG-based movement classification studies, the number of electrodes employed in the systems varies. In literature, 96.7% accuracy is achieved using only one channel s-EMG system [23] while 82% accuracy is obtained using an 8-channel EMG system [24]. The accuracy of the system does not only affected by the number of electrodes. As well as the number of electrodes, it depends on the position of electrodes, the number of movements to be determined, the muscles that will be used while performing related movements, the ADC channel number of the EMG system and the sampling frequency of the system. On the other hand, the number of electrodes of a system can affect the processing time, total cost of modules, power consumption, and dimensions of modules. In this study, we designed a real-time, wearable EMG system. Therefore, by considering the movement detection accuracy as well as processing time, the total cost of modules, power consumption, and dimensions of modules, in this study, we designed a three-channel EMG system. If a higher number of electrodes is used in an EMG system, the accuracy could be upgraded; however, this would increase processing time, the total cost of modules, power consumption, and dimensions of modules.

5. CONCLUSIONS

In this study, a wearable, low-cost, low power consumption and small-size EMG system, which can analyze the finger movements embeddedly and share the commands related to the movements decoded in real-time, was designed for people who have lost their finger movements. A prototype of a 12-bit resolution, wearable s-EMG measurement and classification system was implemented. The system enables to decode finger movements with a short delay of 90ms embeddedly. The system also can transmit the determined finger movements wirelessly through the UDP network protocol on the network it is connected to. The system can work for 4.8 hours with 440 mAh.

The designed prototype showed an average of 99.47% accuracy in offline experiments using the RF algorithm with five different participants, and it was seen that an average of 92.16% accuracy was obtained in online experiments. With the output user interface created with Python, the commands related to the specified finger movements are displayed in real-time with a delay of approximately 90 ms.

The designed system is an important step in the control of EMG-based wearable prosthetic systems, and the design of unmanned vehicles that can be controlled by finger movements. Although the designed wearable EMG system is used to determine the finger movements in this study, the system can be used to classify different movements by making modifications on the system. The performance of the system can be further improved by using different feature selection and classification algorithms.

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DECLARATION OF ETHICAL STANDARDS

The author of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission

AUTHORS' CONTRIBUTIONS

İsmail AYDOĞAN: Responsible for conceptualization, system design and implementation, performing the experiments, data analysis and interpretation of results.

Eda AKMAN AYDIN: Responsible for conceptualization, experiment design, data analysis and interpretation of results.

CONFLICT OF INTEREST: There is no conflict of interest in this study

REFERENCES

[1] Engin K. O. Ç., Bayat O., Duru D. G. and Duru A. D., "Göz hareketlerine dayalı beyin bilgisayar arayüzü tasarımı", ***International Journal of Engineering Research and Development***, 12(1): 176-188, (2020).

[2] Meyns P., Van de Crommert H. W. A. A., Rijken H., Van Kuppevelt D. H. J. M. and Duysens, J. "Locomotor training with body weight support in SCI: EMG improvement is more optimally expressed at a low testing speed" ***Spinal cord***, 52(12): 887-893, (2014).

[3] Fong E. M. and Chung W. Y., "Mobile cloud-computing-based healthcare service by noncontact ECG monitoring" ***Sensors***, 13(12): 16451-16473, (2013).

[4] Ocal H., DOĞRU İ. and BARIŞÇI N, "Internet of Things in Smart and Conventional Wearable Healthcare Devices", ***JOURNAL OF POLYTECHNIC-POLITEKNIK DERGISI***, 22(3), (2020).

[5] Aydin E. A., Bay O. F., & Guler I., "P300-based asynchronous brain computer interface for environmental control system", ***IEEE journal of biomedical and health informatics***, 22(3): 653-663, (2017).

[6] Uşaklı A. B., "Fizyolojik sinyallerin askerî amaçlı kullanılabilirliği: elektroensefalografi ve yakın kızılaltı spektroskopisi örnekleri", ***Politeknik Dergisi***, 21(4): 895-900, (2018).

[7] Kumar S., Dash A. and Mukul, M. K., "Design and development of low-cost eog acquisition circuit for hmi application", ***In 2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN)***, IEEE, 192-197, (2015).

[8] Ferreira A., Celeste W. C., Cheein F. A., Bastos-Filho T. F., Sarcinelli-Filho M. and Carelli R., "Human-machine interfaces based on EMG and EEG applied to robotic systems", ***Journal of NeuroEngineering and Rehabilitation***, 5(1): 1-15, (2008).

[9] Beck T. W. and Housh T. J., "***Use of electromyography in studying human movement***", Routledge, New York, NY, USA, (2008).

[10] TAŞAR B., "***EMG sinyalleri ile çok fonksiyonlu protez el simülatörünün kontrolü/Control of the multifunctional prosthetic hand simulator via EMG signals***", PhD Thesis, Firat University, 2016.

[11] Khan M. U., Aziz S., Sohail M., Shahid A. A. and Samer S., "Automated Detection and Classification of Gastrointestinal Diseases using surface-EMG Signals", ***In 2019 22nd International Multitopic Conference (INMIC)***, IEEE, 1-8, (2019).

[12] Vaca Benitez L. M., Tabie M., Will N., Schmidt S., Jordan M. and Kirchner E. A., "Exoskeleton technology in rehabilitation: Towards an EMG-based orthosis system for upper limb neuromotor rehabilitation", ***Journal of Robotics,*** (2013).

[13] Liu L., Liu P., Clancy E. A., Scheme E. and Englehart K. B., "Electromyogram whitening for improved classification accuracy in upper limb prosthesis control", ***IEEE Transactions on Neural Systems and Rehabilitation Engineering***, 21(5): 767-774, (2013).

[14] Assad C., Wolf M., Stoica A., Theodoridis T. and Glette K., "BioSleeve: A natural EMG-based interface for HRI", ***In 2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)***, IEEE, 69-70, (2013).

[15] Al-Jumaily A. and Olivares R. A., "Electromyogram (EMG) driven system based virtual reality for prosthetic and rehabilitation devices", ***In Proceedings of the 11th International Conference on Information Integration and Web-based Applications & Services,*** 582-586, (2009).

[16] Zhang Z., Yang K., Qian J. and Zhang L., "Real-time surface EMG pattern recognition for hand gestures based on an artificial neural network", ***Sensors***, 19(14): 3170, (2019).

[17] Chandrasekhar V., Vazhayil V. and Rao M., "Design of a real time portable low-cost multi-channel surface electromyography system to aid neuromuscular disorder and post stroke rehabilitation patients", ***In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)***, sIEEE, 4138-4142, (2020).

[18] Antfolk C., Cipriani C., Controzzi M., Carrozza M. C., Lundborg G., Rosén B. and Sebelius F., "Using EMG for real-time prediction of joint angles to control a prosthetic hand equipped with a sensory feedback system" ***Journal of Medical and Biological Engineering***, 30(6): 399-406, (2010).

[19] Malešević N., Marković D., Kanitz G., Controzzi M., Cipriani C. and Antfolk C., "Vector autoregressive hierarchical hidden Markov models for extracting finger movements using multichannel surface EMG signals" ***Complexity***, (2018).

[20] Yamanoi Y., Ogiri Y., & Kato R., "EMG-based posture classification using a convolutional neural network for a myoelectric hand" ***Biomedical Signal Processing and Control***, 55: 101574, (2020).

[21] Mayetin U., Küçük S. and Şayli Ö., "EMG controlled mobile robot application" ***In 2015 Medical Technologies National Conference (TIPTEKNO),*** IEEE, 1-4, (2015).

[22] Onay F. and Mert A., " Phasor represented EMG feature extraction against varying contraction level of prosthetic control", ***Biomedical Signal Processing and Control***, 59: 101881, (2020).

[23] Ariyanto M., Caesarendra W., Mustaqim K. A., Irfan M., Pakpahan J. A., Setiawan J. D. and Winoto A. R., "Finger movement pattern recognition method using artificial neural network based on electromyography (EMG) sensor" ***In 2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology (ICACOMIT)***, IEEE, 12-17, (2015).

[24] Caesarendra W., Tjahjowidodo T., Nico Y., Wahyudati S. and Nurhasanah L., "EMG finger movement classification based on ANFIS", ***In Journal of Physics: 3conference series***, 1007(1): 012005, (2018).

[25] Bonato P. (2005), "Advances in wearable technology and applications in physical medicine and rehabilitation", ***Journal of neuroengineering and rehabilitation***, 2(1): 1-4, (2005).

[26] Liu X., Sacks J., Zhang M., Richardson A. G., Lucas T. H. and Van der Spiegel J., "The virtual trackpad: An electromyography-based, wireless, real-time, low-power, embedded hand-gesture-recognition system using an event-driven artificial neural network", ***IEEE Transactions on Circuits and Systems II: Express Briefs***, 64(11): 1257-1261, (2016).

[27] Benatti S., Casamassima F., Milosevic B., Farella E., Schönle P., Fateh S., Burger T., Huang Q. and Benini L., "A versatile embedded platform for EMG acquisition and gesture recognition", ***IEEE transactions on biomedical circuits and systems,*** 9(5): 620-630, (2015).

[28]Https://Espressif.Com/Sites/Default/Files/Documentation/0a-Esp8266ex_Datasheet_En.Pdf

[29] https://pypi.org/project/micromlgen/, "micromlgen 1.1.23", (2021).

[30] Protocol U. D., "Rfc 768 j. postel isi 28 august 1980.", ***Isi,*** (1980).

[31] Duda R. O., Hart P. E. and Stork D. G., "***Pattern Classification"***, Wiley, USA 49-53 2012

[32] Baranauskas J., Oshiro T. and Perez, P. (2012), "How Many Trees in a Random Forest. Machiene learning", ***Machine Learning and Data Mining in Pattern Recognition***, 154-168, (2012).

[33] Leonardis D., Barsotti M., Loconsole C., Solazzi M., Troncossi M., Mazzotti C., Castelli V. P., Procopio C., Lamola G., Chisari C., Bergamasco M. and Frisoli A., "An EMG-Controlled Robotic Hand Exoskeleton for Bilateral Rehabilitation", ***IEEE transactions on haptics***, 8(2): 140–151, (2015).

[34] Sadikoglu F., Kavalcioglu C. and Dagman B., "Electromyogram (EMG) signal detection, classification of EMG signals and diagnosis of neuropathy muscle disease", ***Procedia computer science***, 120: 422-429, (2017).

[35] Hardalaç F. , Poyraz M., "Yapay Sinir Ağları Kullanılarak EMG Sinyallerinin Sınıflandırılması ve Neuropathy Kas Hastalığının Teşhisi", ***Politeknik Dergisi***, 2002; 5(1): 75-83.

[36] Ali M., Riaz A., Usmani W. U. and Naseer N., "EMG Based Control of a Quadcopter", ***In 2020 3rd International Conference on Mechanical, Electronics, Computer, and Industrial Technology (MECnIT),*** IEEE, 250-254, (2020).