International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 6, December 2024, pp. 6526~6537
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i6.pp3526-6537

Processing of real-time surface electromyography signals during knee movements of rehabilitation participants

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Article Info

Article history:

Received Jun 10, 2024
Revised Jul 15, 2024
Accepted Aug 6, 2024

Keywords:

Knee movement
NI-myRIO
Rehabilitation
sEMG
Signal processing
Vastus lateralis
Vastus medialis

ABSTRACT

In this work, we present a knee rehabilitation system focusing on the processing of surface electromyography (sEMG) signals measured from the vastus lateralis (VL) and vastus medialis (VM) muscles of rehabilitation participants. A two-channel electromyography (EMG) device and the NI-myRIO embedded device are used to collect real-time sEMG signals in accordance with pre-designed rehabilitation programs. The novelty and contribution of this work is that we develop an sEMG processing function where real-time sEMG data are automatically processed and sEMG results of both VL and VM in terms of root mean square value (RMS), different RMS levels of VL and VM, and maximum RMS for each round of knee movements are provided. The results here indicate how well the rehabilitation users can move their knees during rehabilitation, referring to knee and muscle performances. Experimental results from healthy participants show that we can automatically and efficiently collect and monitor rehabilitation results, allowing rehabilitation participants to know how their knees performed during testing and medical experts to evaluate and design treatment.

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1. INTRODUCTION

Knee movement performance is essential for human health and wellbeing [1]. Since many daily human activities all involve the knee, knee injuries and degeneration can significant affect daily life duties [2], [3]. In addition, aging and the development of certain disorders, such as osteoarthritis (OA), can also result in knee performance deterioration [4]–[6]. To improve knee movement performance, rehabilitation for enhancing the knee muscles is an important treatment. Not only OA, but additional illnesses and symptoms are associated with knee joint mobility difficulties. Thus, related people in this group need effective rehabilitation treatment [2], [7]. Moreover, accurate measurement of knee extension and flexion muscle strength is also essential for assessing the impact of treatment solutions or training sessions [8], [9].

Because of the significance of the mentioned issues, effective techniques and solutions to aid human knee joint mobility are necessary. Electromyography (EMG), offers information regarding muscle activity [10]. Therefore, EMG devices can be utilized for satisfying this requirement and application. EMG is used to assess muscle behavior throughout the task [11], based on changes in the electrical signal [12], [13]. The literature review on the development of knee joint monitoring and rehabilitation systems based on EMG is discussed below. Table 1 also summarizes a comparison of existing works and this work.

Table 1. Comparison of this work and related works

Works	Major objective and function
[14]	The prediction method using sEMG signal for dynamic knee joint range of motion
[15]	A method for measuring knee joint resistive torque using an isokinetic machine
[16]	The EMG angle relationship of the quadriceps muscle during knee extension
[17]	The association between isometric force and sEMG of the quadriceps femoris muscles during single-joint knee extension and multi-joint leg push activities
[18]	Knee movement estimation from sEMG using random forest with the PCA method
[19]	Knee joint angle estimation in the lower limb utilizing sEMG signals
[20]	The sEMG-based estimate model for knee joint angle
[6]	The development of the knee monitoring and rehabilitation system using a two-channel sEMG device and the monitoring of sEMG signals
[21]	Monitoring of sEMG signals in terms of statistical data (i.e., minimum value, maximum value, mean, median, mode, standard deviation, and skewness)
This work	- The development of the processing function using real-time VL and VM sEMG - The rehabilitation outputs, indicating how well the rehabilitation users can move their knees during rehabilitation, were determined and reported.

The prediction method using surface EMG (i.e., sEMG) signals for dynamic knee joint range of motion (ROM) based on the external load applied during leg extension was presented in [14]. The authors summarized how the ROM changed in relation to the external loads throughout exercise and proposed that their approaches could be used as rehabilitation procedures. The work in [15] presented a method for measuring knee joint resistive torque using an isokinetic machine (i.e., Biodex). The sEMG signals were monitored simultaneously using the monitoring potentiometer outputs installed on the Biodex arm.

In study [16], muscular activity during knee extension was examined using elastic tubing and isotonic resistance, with the main objective of determining the sEMG angle relationship of the quadriceps muscle during knee extension. The system was tested by nine men and seven women. During knee extension, the knee joint angle was determined with inclinometers, and sEMG was collected simultaneously. The peak sEMG of the vastus lateralis (VL), vastus medialis (VM), and rectus femoris (RF) muscles showed no changes during the concentric contraction phase. The study in [17] also investigated the association between isometric force and sEMG of the quadriceps femoris muscles during single-joint knee extension and multi-joint leg push activities. Nine healthy participants performed their activities at a knee angle of 90° at 20% to 100% maximal contraction, with the VL, VM, biceps femoris (BF), and RF muscles targeted for sEMG recording. The authors found that all of the muscles studied had a similar sEMG/force relationship at a 90° angle to the knee.

Li *et al.* [18] proposed the estimation of knee movement from sEMG utilizing random forest with principle component analysis (PCA). The sEMG signals associated with knee motions during normal walking in people were assessed, where considered muscles included VL, VM, RF, gastrocnemius medialis (GM), and gastrocnemius lateralis (GL). The authors determined that their proposed methods could estimate knee motion more accurately than the back propagation neural network with the PCA model. The study in [19] also enhanced the estimation accuracy of the knee joint angle in the lower limb utilizing sEMG signals. The PCA and regularized extreme learning machine (RELM) were used to calculate continuous knee motion. The sensor placements targeted the MF, RF, LF, BF, semitendinosus (SE), and gastrocnemius muscles. As reported by the authors, the RELM technique not only ensured the validity of results but also reduced learning time. Yang *et al.* [20] also suggested a sEMG-based estimate model for knee joint angle. Six sEMG channels from important muscles (i.e., BF, RF, VL, VM, SE, and gracilize) were recorded. Predictive models included a back propagation neural network and a least-square support vector regression machine (LS-SVR). The results showed that such a method performed effectively for the knee-joint angle in all types of leg motions.

Finally, as in our previous works [6] and [21], we developed a knee monitoring and rehabilitation system based on sEMG, measuring the sEMG of VL and VM muscles according to rehabilitation programs. The experimental results revealed real-time sEMG signals, with the primary objective of the study in [6]. In [21], sEMG results were reported in terms of statistical data such as minimum value, maximum value, mean, median, mode, standard deviation, and skewness. However, the processing functions of sEMG signals in terms of continuous rehabilitation results, which indicate how well rehabilitation users can move their knees throughout rehabilitation, were not considered.

According to the previous literature analysis, in this work, we describe a knee rehabilitation system focused on the processing of sEMG signals to assist rehabilitation participants and medical specialists. This work provides two key contributions and novelties.

- First, the processing function using real-time VL and VM sEMG inputs is developed, where the rehabilitation outputs, indicating how well the rehabilitation users can move their knees during rehabilitation, are automatically determined and reported.

– Second, the proposed solution has been tested with healthy participants. Both rehabilitation participants and medical experts can observe and assess rehabilitation results during testing. Our proposed system and solutions can provide not only real-time measurement data but also summarized rehabilitation results, assisting individuals with healthcare applications.

The structure of this paper is organized as follows: section 2 presents methods including a knee rehabilitation system, sEMG data collection, and the processing of sEMG data (i.e., the proposed solution). Results and discussion are provided in section 3, and the paper is concluded in section 4.

2. METHOD

2.1. Knee rehabilitation system

A proposed knee rehabilitation system is presented in Figure 1. Rehabilitation users sit in a chair with a sandbag attached to the ankle to increase the load on the knee during rehabilitation. Two-channel sEMG electrodes are attached to the VL and VM muscles, where they are linked to the sEMG circuit and connected to the NI-myRIO as the processing unit [22], [23]. In the NI-myRIO, the LabVIEW program is employed to implement knee rehabilitation programs, which are recommended by physiotherapists and physicians. We note that details of this system's implementation can be found in [6]. The NI-myRIO also processes raw sEMG signals (VL sEMG and VM sEMG), with signal patterns that match pre-designed rehabilitation programs. These signals will be sent to the processing function implemented in the LabVIEW program to determine the final rehabilitation results to support rehabilitation users and medical experts. The processing function processes real-time sEMG signals and returns sEMG data for both VL and VM in terms of RMS values, different RMS levels of VL and VM, and maximum RMS for each round of knee movements. They will be further described in section 2.3. Such rehabilitation results will be collected in the database and displayed on the computer. With our solution, rehabilitation users can monitor their knee performances during testing, and medical experts can also evaluate and design treatment as feedback for users.

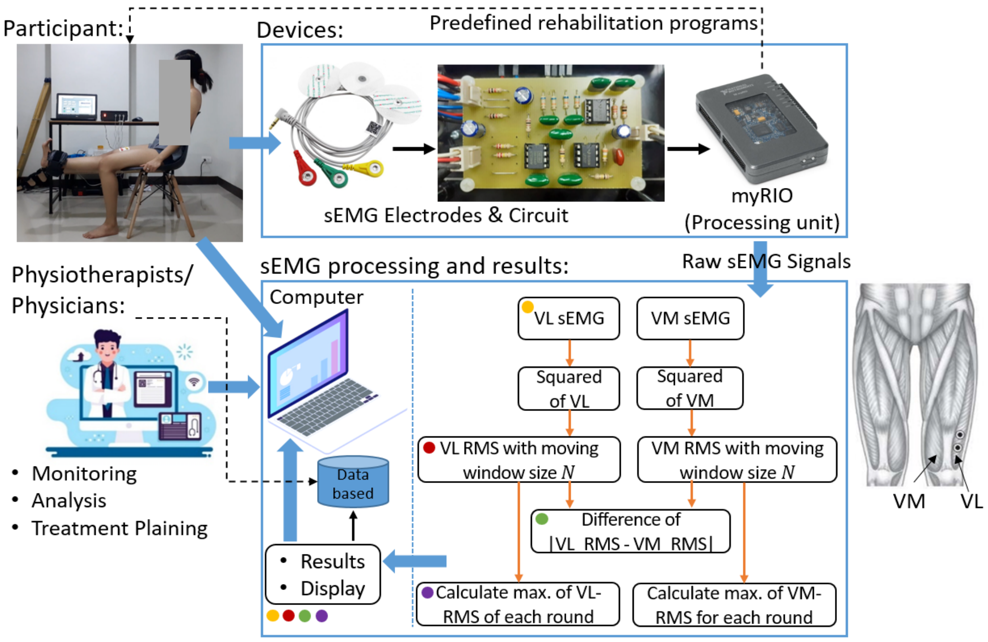


Figure 1. A proposed knee rehabilitation system

2.2. sEMG data collection

For sEMG data collection, as demonstrated in Figure 2, a rehabilitation participant will be advised to sit in the optimal position and posture recommended by experts. The sandbag is attached to the ankle, and its weight can be adjusted based on the experts' recommendations. Two electrodes are attached to the VL and VM muscles, with one placed on the hand or forearm as a reference electrode. The system was tested by three healthy participants, and Table 2 displays the participant's data, such as gender, age (year), weight (kg), and the knee sides to be tested.

Table 2. Participant's data [6]

Subjects	1	2	3
Gender	Male	Male	Female
Age (year)	35	31	30
Weight (kg)	65	67	49
Knee's side	Right	Left	Right

For each round of the test, the participant will move the leg from 0 to 90 degrees, with the subject seated and fully extending the knee. According to experts, the VL and VM muscles were the targets for testing because of their importance in patellar stability during knee extension. These muscles are closely linked to knee pain and performance. Figure 2 depicts a knee movement pattern. The participant begins with a 0 degrees knee position and then moves the knee to 90 degrees, or the maximum degree that the participant is capable of [6], [24], [25]. The participant keeps his or her knee at its highest point for a period of time and then returns to the starting position and takes a little rest [26]–[30]. This refers to single-round testing. The participant can proceed to the following round until they reach the last round or one set. There are five rounds for this work.

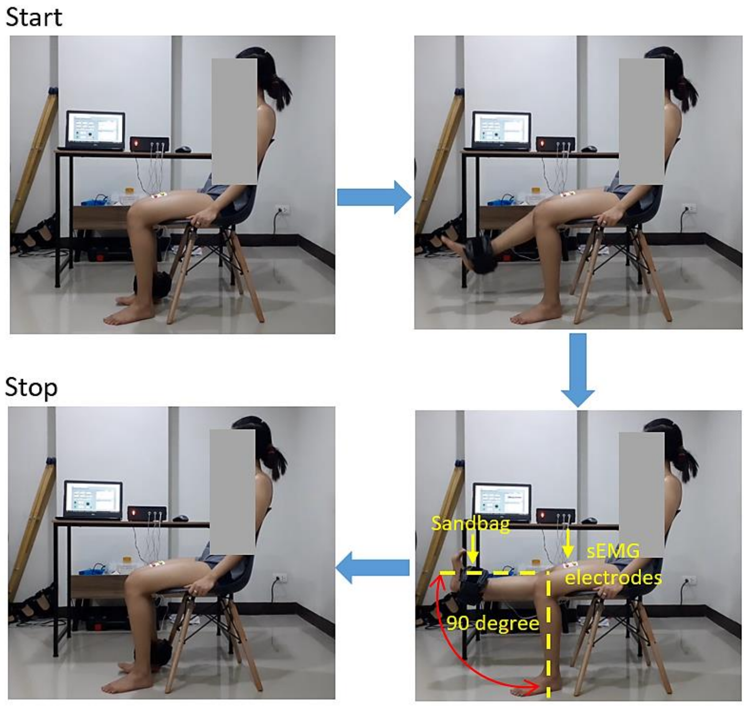


Figure 2. Knee movements for a one-round test

2.3. Processing of sEMG data (the proposed solution)

As mentioned in section 2.1, raw VL and VM sEMG signals according to pre-designed rehabilitation programs are sent to the sEMG processing function to determine the final rehabilitation results, including i) RMS values of VL and VM (i.e., VL_RMS_i and VM_RMS_i), ii) different levels of VL RMS and VM RMS (i.e, ΔV_RMS_i), and iii) maximum VL RMS and VM RMS for each round of knee movements (i.e., $VL\_RMSmax_{round(j)}$ and $VM\_RMSmax_{round(j)}$). The results here can refer to knee and muscle performances. The RMS values show the mean sEMG aptitudes for each time period (window size) measured from the VL and VM muscles. The difference between VL and VM RMS indicates the amplitude level of VL and VM muscles during flexion and extension, as well as the balance between those muscles. Finally, the maximum VL and VM RMS for each round of knee movements will indicate how well the rehabilitation users can consistently move their knees from the first round to the final round. With our proposed solution, both users and medical specialists can utilize the rehabilitation results to monitor and focus their attention on the precise data they want to observe.

The VL_RMS_i and VM_RMS_i with the window size N are calculated using (1) and (2), where VL_sEMG_i and VM_sEMG_i are the raw sEMG data and N is set to 1,000 samples in this work (0.001 s for each sEMG sample, 1 s for each window). ΔV_RMS_i is expressed in (3). Finally, the maximum values of VL RMS and VM RMS for round 1 to round 5 of knee movements are shown in (4) and (5), respectively. Figure 3 also illustrates the block diagram for the sEMG processing function implemented in the LabVIEW program on NI myRIO. We note that (4) and (5) are calculated under the time condition in (6), where the optimal time periods can be automatically set based on the rehabilitation programs advised by the medical experts.

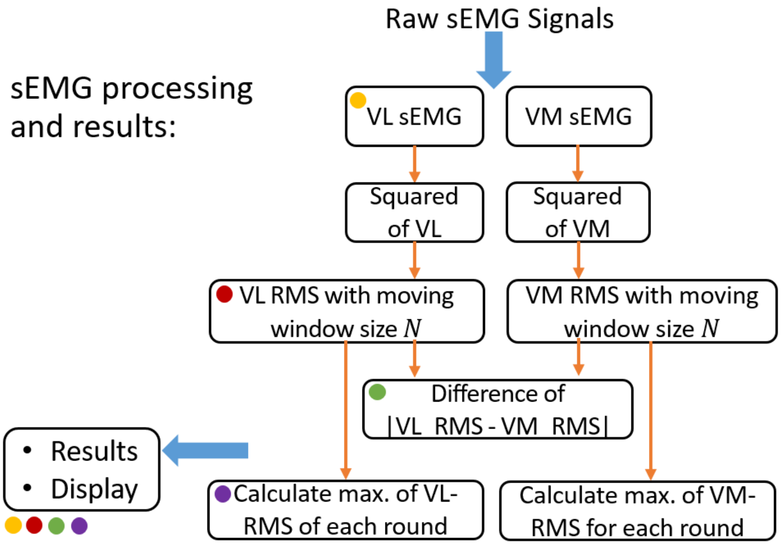


Figure 3. Block diagram for the sEMG processing function

$$VL\_RMS_i = \sqrt{\frac{1}{N}\sum_{i-N+1}^{N}(VL\_sEMG_i)^2}\ ; i \geq N$$

$$VL\_RMS_i = \sqrt{\frac{VL\_sEMG_i{}^2 + VL\_sEMG_{i-1}{}^2 + \cdots VL\_sEMG_{i-N+1}{}^2}{N}}\ ;\ i \geq N \tag{1}$$

$$VM\_RMS_i = \sqrt{\frac{1}{N}\sum_{i-N+1}^{N}(VM\_sEMG_i)^2}\ ; i \geq N$$

$$VM\_RMS_i = \sqrt{\frac{VM\_sEMG_i{}^2 + VM\_sEMG_{i-1}{}^2 + \cdots VM\_sEMG_{i-N+1}{}^2}{N}}\ ;\ i \geq N \tag{2}$$

$$\Delta V\_RMS_i = |VL\_RMS_i - VM\_RMS_i|; i \geq N \tag{3}$$

$$VL\_RMSmax_{round(j)} = max.\left(VL\_RMS_{i\to t_j}, \ldots VL\_RMS_{i\to t_{j+1}}\right); j \to 1 \text{ to } 5$$

$$VL\_RMSmax = [VL\_RMSmax_{round(1)}, VL\_RMSmax_{round(2)}, \ldots VL\_RMSmax_{round(5)}] \tag{4}$$

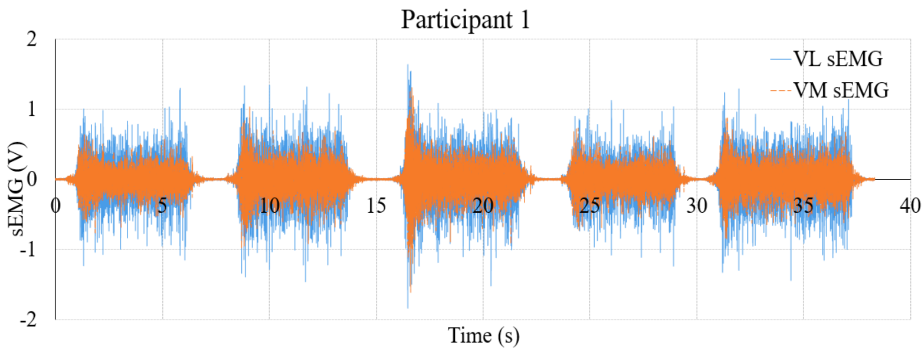
$$VM\_RMSmax_{round(j)} = max.\left(VM\_RMS_{i\to t_j}, \ldots VM\_RMS_{i\to t_{j+1}}\right); j \to 1 \text{ to } 5$$

$$VM\_RMSmax = [VM\_RMSmax_{round(1)}, VM\_RMSmax_{round(2)}, \ldots VM\_RMSmax_{round(5)}] \tag{5}$$

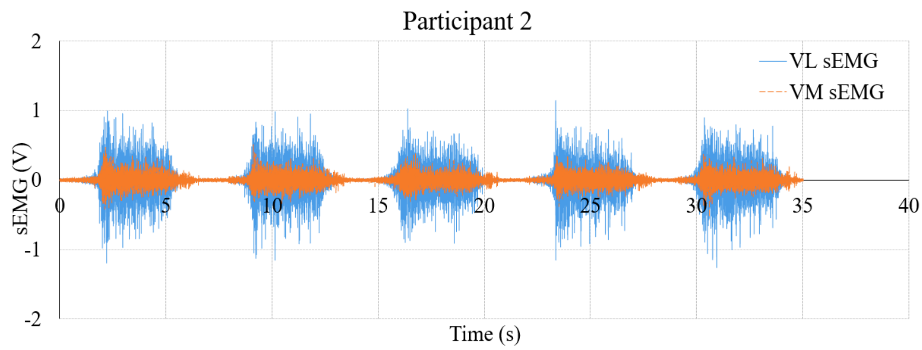
$$round(j) = \begin{cases} 1;\ for \to\ t_1 \leq t \leq\ t_2 \\ 2;\ for \to\ t_2 < t \leq\ t_3 \\ 3;\ for \to\ t_3 < t \leq\ t_4 \\ 4;\ for \to\ t_4 < t \leq\ t_5 \\ 5;\ for \to\ t_5 < t \leq\ t_6 \end{cases} \to round(j) = \begin{cases} 1; for \to\ 0\,s \leq t \leq 8\,s \\ 2; for \to\ 8\,s < t \leq 16\,s \\ 3; for \to 16\,s < t \leq 24\,s \\ 4; for \to 24\,s < t \leq 32\,s \\ 5; for \to 32\,s < t \leq 40\,s \end{cases} \tag{6}$$

3. RESULTS AND DISCUSSION

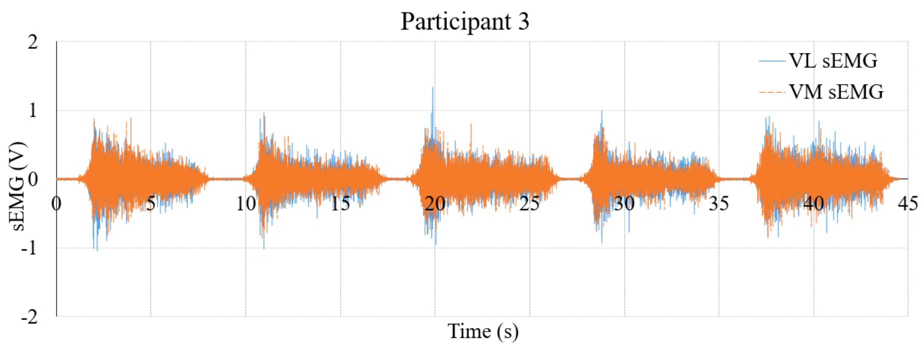
Figures 4(a) to (c) depict the raw VL and VM sEMG signals of participants 1–3, as given by the sEMG device and myRIO. The findings show that sEMG signals follow the knee movement pattern and the rehabilitation program. There are five rounds of testing in which VL and VM amplitudes are detected when participants move their knee joints against the weight of the sandbag. VL and VM RMS results are also demonstrated in Figures 5(a) to (c). As shown by the results, participant 1 can continuously move his knee with high sEMG amplitudes for longer periods of time throughout all testing protocols. Unlike participant 2, he can move his knee in a shorter period of time, as shown by the sEMG signals in Figure 4(b). Participant 3 can move her knee for a longer period of time, although her signal amplitudes are lower than those of participant 1. This discussion is supported by the VL and VM RMS data in Figures 5(a) to (c) and Figures 6(a) and (b). As shown in Figures 5(a) to (c), concentrating on the continuous RMS signal patterns, participant 1's RMS signal reaches its maximum amplitude when he moves his knee to 90 degrees. The amplitude does not drop suddenly before returning his knee to 0 degrees. Compared to participant 2, the RMS signals decrease fast, indicating that he can hole his knee at 90 degrees in less time. The illustration in Figures 6(a) and (b) focuses on 25 seconds or three rounds of testing, which validates the previous explanation.



(a)



(b)



(c)

Figure 4. VL and VM sEMG signals: (a) participant 1, (b) participant 2, and (c) participant 3

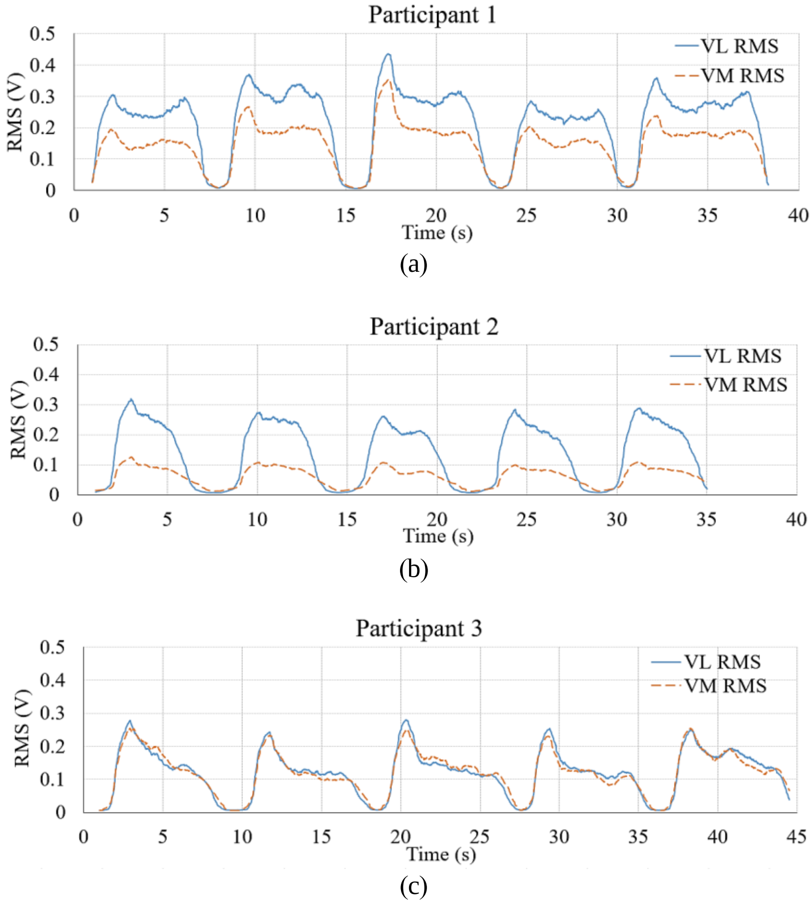


Figure 5. VL and VM RMS results: (a) participant 1, (b) participant 2, and (c) participant 3

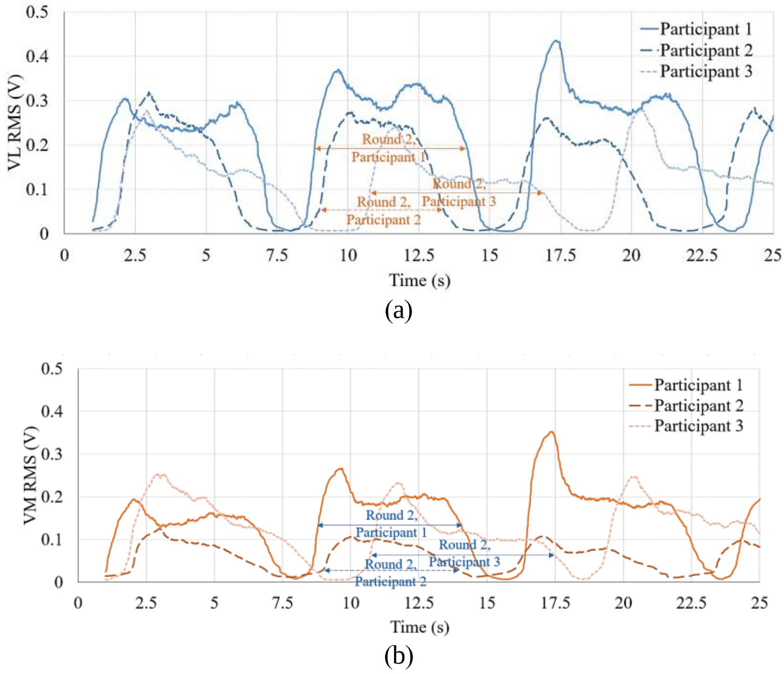
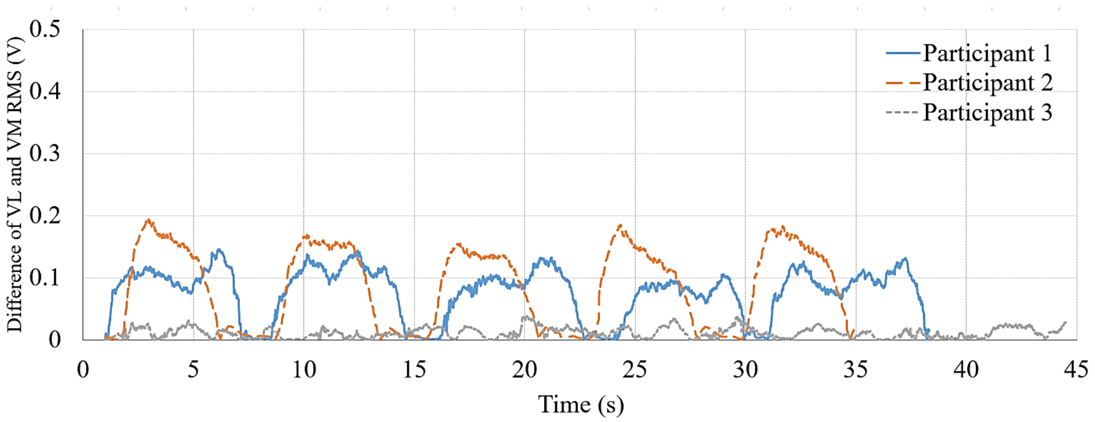
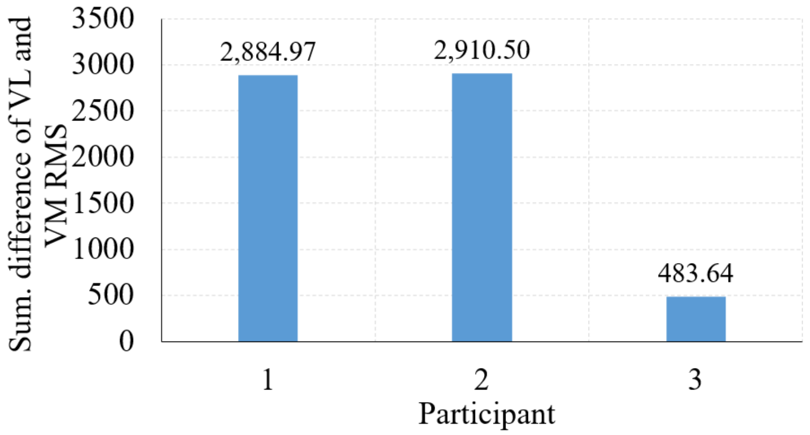


Figure 6. Comparison of VL RMS and VM RMS for participants 1 to 3 (only for rounds 1 to 3): (a) VL RMS and (b) VM RMS

The previous results also show that the signals from the VL muscle are bigger than the VM signals measured from participants 1 and 2. For participant 3, there is little difference between VL and VM signals. Figures 7(a) and (b) show the different levels of VL RMS and VM RMS among all participants. Participant 2 has a greater VL RMS than VL RMS (quite small), hence the difference in level is large. In the case of participant 3, the VL RMS and the VM RMS are very close, as seen in Figure 5(c). Thus, the difference is quite small compared to other participants. We note that the summation of the different VL and VM RMS levels is also illustrated in Figure 7(b). The data in Figures 7(a) and (b) can be used by physiotherapists and physicians to investigate knee performance and muscle activity.



(a)



(b)

Figure 7. Illustration of different levels of VL RMS and VM RMS and summation of different VL and VM RMS levels for participants 1 to 3: (a) difference between VL RMS and VM RMS, and (b) summation of different levels

Figures 8(a) to (c) depicts the maximum VL RMS and VM RMS from five rounds of knee movements performed by participants 1–3. The results show how well the participants can move their knees consistently from the beginning to the last round. As seen in Figure 8(a), participant 1 uses greater power to move his knee in round 3, as the VL and VM RMS are higher than in previous rounds. In this example, participants 2 and 3 produced consistent results. For example, participant 2 achieves maximum VL RMS values of 0.32, 0.27, 0.26, 0.28, and 0.29 from rounds 1 to 5, whereas participant 1 achieves 0.31, 0.37, 0.44, 0.29, and 0.36, respectively. We can see that, while participant 1 has more power to move his knee with high sEMG levels, the sEMG levels vary from round to round.

Figures 1 to 8 provide more investigation information and a better understanding of the user's rehabilitative behavior. As shown in Figure 9, final rehabilitation outcomes are provided to rehabilitation users and medical professionals. As a result, our system and methodology can gather and monitor rehabilitation data in an automated and efficient manner, allowing rehabilitation participants to understand how their knees performed during testing and medical specialists to evaluate and plan treatment.

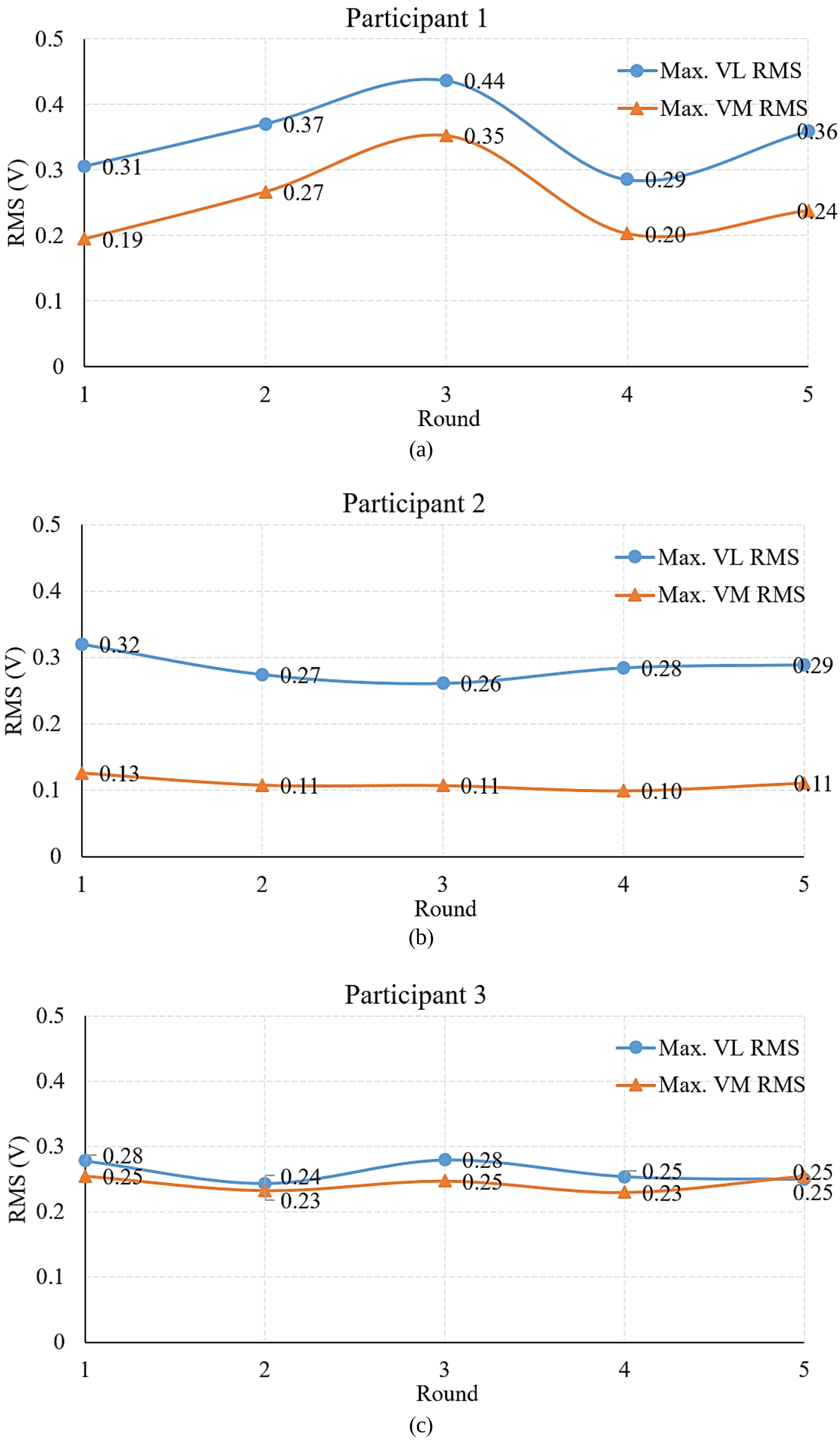


Figure 8. Maximum VL RMS and VM RMS for each round of knee movements: (a) participant 1, (b) participant 2, and (c) participant 3

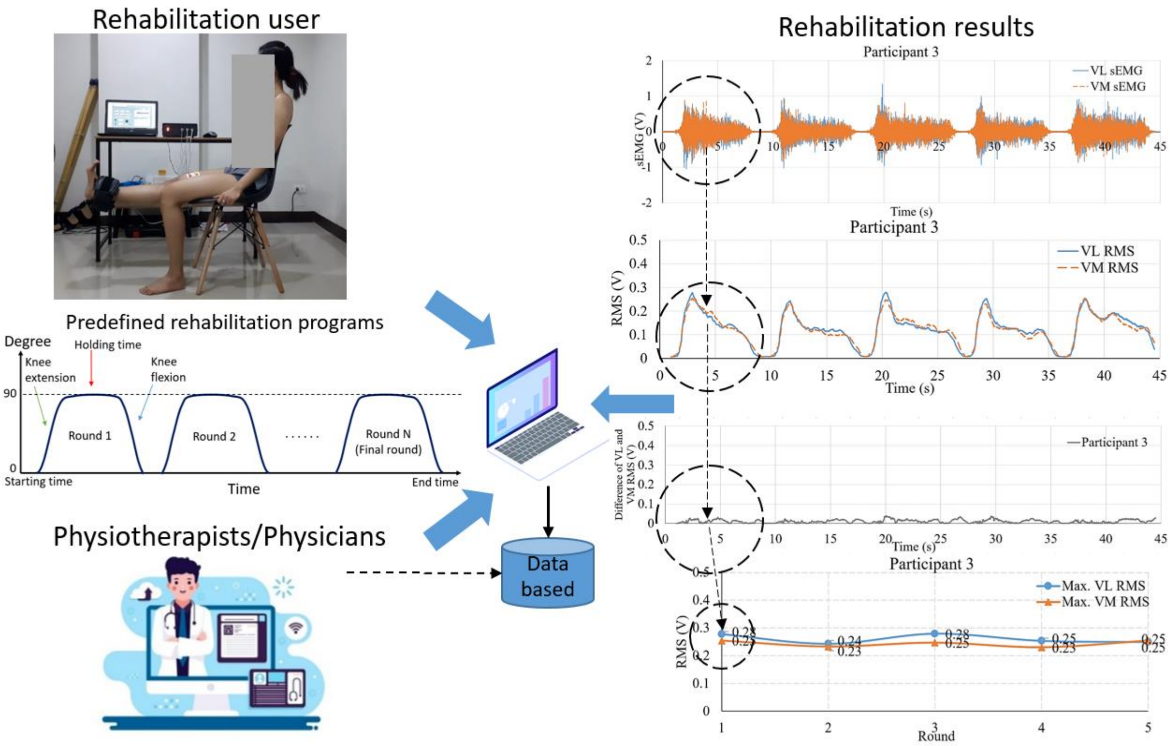


Figure 9. Illustration of final rehabilitation results for rehabilitation users and medical experts

4. CONCLUSION

This paper introduces the processing of sEMG signals obtained from the VL and VM muscles of knee rehabilitation users. We developed a sEMG processing procedure that automatically processes real-time VL and VM sEMG data collected during rehabilitation programs. The rehabilitation results for users and medical experts are VL RMS, VM RMS, different RMS levels of VL and VM, and the maximum RMS for each cycle of knee motions. The data shown here refer to knee and muscle performance during rehabilitation. The experimental results demonstrate the suggested system's efficiency in collecting and monitoring sEMG data, allowing rehabilitation users to know their knee performance during testing and medical specialists to evaluate and develop treatment. In future work, the proposed system and solution will be tested with both healthy participants and patients with knee movement problems. The results from both groups of participants will be reported for assessment.

ACKNOWLEDGEMENTS

This research was supported by National Science, Research and Innovation Fund (NSRF) and Prince of Songkla University (Ref. No. ENG6701305S)

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