IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 29 April 2024, accepted 14 May 2024, date of publication 24 May 2024, date of current version 6 June 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3405315

RESEARCH ARTICLE

Muscle Innervation Zone Localization: A Linearity Measure-Based Approach With Applications to Post-Stroke Plasticity and Episiotomy

KHALIL ULLAH[1], SULAIMAN ALMUTAIRI[2], RIAZ AHMAD[3], SIRAJ MUHAMMAD[3], ABDALLAH NAMOUN[4], (Member, IEEE), AND ISA ALI IBRAHIM[5]

[1]Department of Software Engineering, University of Malakand, Chakdara, Khyber Pakhtunkhwa 18800, Pakistan
[2]Department of Health Informatics, College of Applied Medical Sciences, Qassim University, Buraydah, Al Qassim 51452, Saudi Arabia
[3]Department of Computer Science, Shaheed Benazir Bhutto University Sheringal, Upper Dir, Khyber Pakhtunkhwa 18050, Pakistan
[4]Faculty of Computer and Information Systems, Islamic University of Madinah, Madinah 42351, Saudi Arabia
[5]Department of Cybersecurity, School of Information and Communication Technology, Federal University of Technology Owerri, Owerri 460114, Nigeria

Corresponding authors: Siraj Muhammad (msiraj83@sbbu.edu.pk) and Isa Ali Ibrahim (ibrahim.ali@futo.edu.ng)

This work was supported by the King Salman Center for Disability Research through Research Group under Grant KSRG-2023-560.

ABSTRACT Localization of motor unit (MU) innervation zones (IZs) is an important step in several clinical and non-clinical applications, such as 1) acquisition of surface electromyogram (sEMG) signal for accurate estimation of its amplitude and other parameters by avoiding placing electrodes on IZs, 2) accurate estimation of the EMG-Force relationship, 3) effective injection of Botulinum Toxin in Post-stroke Spasticity near the IZs, and 4) guiding obstetricians to perform episiotomy during child delivery by avoiding cutting near the IZs of External Anal Sphincter (EAS) muscle. The most minimally invasive way to identify the location of motor unit innervation zones (IZs) in any muscle, including the External Anal Sphincter (EAS) muscle, is to use multi-channel surface electromyography (sEMG) signals. In this manuscript, we propose a novel approach for automatic muscle motor unit innervation zone localization using multi-channel electromyography (EMG) signals. Our method is based on a linearity measure derived from eigenvalues of the Hessian matrix. The motor unit action potential (MUAP) propagation pattern is first detected in the spatio-temporal sEMG images using a Linearity measure based on eigenvalues of the Hessian matrix. The corresponding MU IZs is then identified as the starting point of propagation of the MUAP. A software is also developed which can be used to record and visualize the signals acquired from EAS and other muscles, detect, and display the IZs and more importantly compute and display the histogram of the IZs and generate reports which will help the obstetrician while performing episiotomy during child delivery to avoid cutting vulnerable regions that may lead to fecal incontinence at later age. The evaluations,on both simulated and experimental EMG signals, demonstrate the effectiveness and robustness of our proposed approach. Compared to existing methods, our approach achieves higher accuracy in innervation zone localization on experimental and simulated signals with mean absolute error of 0.53 and 0.53 inter electrode distance (IED).

INDEX TERMS EMG signals, spatio-temporal image, eigenvalue, Hessian matrix, linearity measure, innervation zone.

I. INTRODUCTION

The motor unit (MU) is a fundamental component of a muscle and is made up of a motor neuron and several fibres it innervates. The motor unit innervation zone (MU-IZ) is a region where a lot of neuromuscular connections that belong to the same MU are dispersed (see Fig. 1a). Each MU has one IZ in addition to several neuromuscular connections. One or more IZs may exist in a muscle. At every neuromuscular junction, where a fibre is innervated, an electrical potential begins and runs in the fibres in opposition to one another called fiber potential. The motor unit action potential (MUAP) is

The associate editor coordinating the review of this manuscript and approving it for publication was Jinhua Sheng.

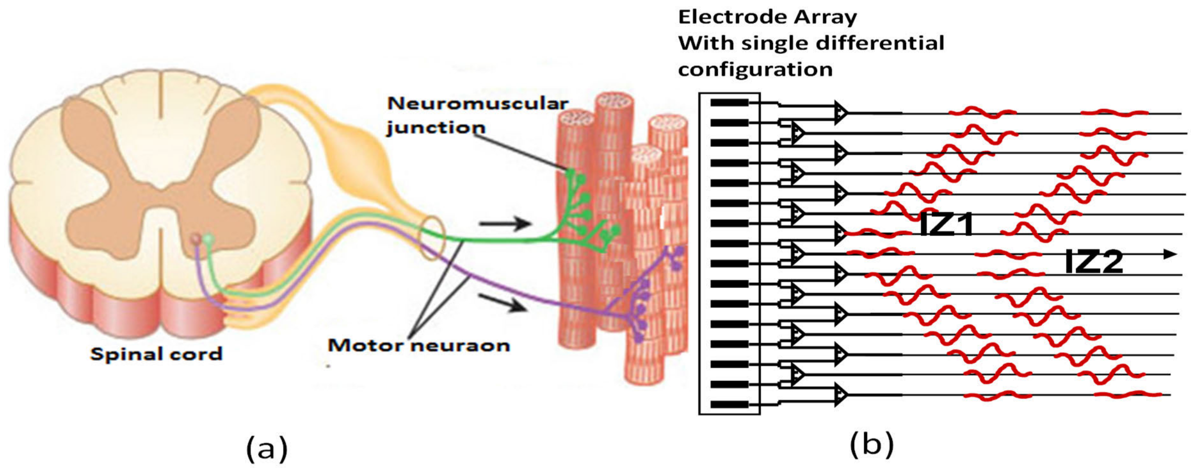


FIGURE 1. a) A motor unit (MU) composed of a motor neuron and its corresponding muscle fibers. The MU-IZ is the region of space where the neuromuscular junctions are located [image courtesy of Pearson publications], b) The sEMG consisted of MUAPs acquired with an electrodes array placed parallel to the muscle fibers with a bipolar electrode arrangement.

a collection of these fibre potentials from the same MU. When muscle fibres are along the skin, as in Fig. 1b, we may see the MUAP pattern in the sEMG signal collected with an electrode array placed parallel to the muscle fibre on the skin. The MU-IZ is the starting point of the bidirectional MUAP propagation. High density sEMG signals from various skeletal and non-skeletal muscles exhibit this type of MUAP propagation pattern [1]. If one end of the electrode array is near the IZ, then instead of bidirectional propagation, unidirectional MUAP propagation can be seen in the acquired EMG signals [2]. This is very common in the EMG signal of the External Anal Sphincter (EAS) muscle [2]. The aim of this research is to automatically detect the MU IZ of different muscles from multi-channel EMG.

Since the sEMG amplitude is smaller when the electrodes are over the IZs in single differential configurations, collecting sEMG at the innervation zone may result in inaccurate estimation of the EMG amplitude parameters such as the root mean square (RMS) value, average rectified value (ARV), and other significant parameters of the EMG signals [1]. For proper assessment of these parameters, which will result in accurate estimation of the physiological and anatomical information of the muscle, the identification of the IZ is therefore important prior to recording the EMG signals. Also, In order to control exoskeletal, rehabilitative, and prosthetic robots, sEMG is also employed to quantify muscle force [3]. Since they take into consideration the spatial variation of the sEMG signal in the muscle, recently created methods using multi-channel signals for estimating muscle force have greatly improved the force estimation [4]. Recent research has discovered that the electrodes' placement across the IZs region alters the EMG amplitude parameters, which in turn influences the force estimates. Therefore, IZs localisation is crucial for exoskeletal and prosthetic device control. According to a recent study in [5], the channels having IZs had a higher percentage of faulty channels when it came to EMG to Force modelling. The placement of electrodes over IZs should be avoided to obtain a constant EMG-Force connection, and this can only be done if the position of the IZs is known. Obstetricians and medical professionals can detect the area around the EAS muscle vulnerable to perform episiotomy by determining the position of IZs of the external anal sphincter (EAS) muscle during episiotomy during childbirth. According to several studies [6], [7], and [8], there is a strong correlation between women's EAS incontinence and EAS injury in cases of episiotomy after vaginal childbirth. Those who have an episiotomy during childbirth are more likely to have faecal incontinence than women who don't have damaged EAS nerves [9]. The risk of nerve tears during child delivery or obstetric is discussed to a greater extent in literature, however, the best location for performing the episiotomy is yet to be determined due to large number of variations in the MU-IZs from woman to woman. Thus to guide episiotomy in a good way, the MU-IZ of EAS muscle of each individual subject should be detected first and then a possible location (middle, left, right) of the vagina, can be suggested for the cutting, or cutting may be considered too dangerous and avoided. Poststroke spasticity is considered as emerging health problem for stroke fighters [10]. Botulinum toxin remains the first line treatment for focal spasticity management. In recent research in [11], it was found that precise injection near the MU-IZs increase the effect of Botulinum neurotoxin type A (BoNT-A) and thus reduces the dosage and expense. They also claimed that near the MU-IZ injection reduces the BoNT-A dose into the and optimizes the therapy effect of BoNT-A. It also minimizes the side effects such as undesirable weakness of the nearby muscles.

The identification of MU-IZs is crucial in the aforementioned clinical and non-clinical applications. Although an expert can locate IZs by visually examining the bipolar signal, this method is time consuming thus not applicable for real-time applications; hence, algorithms are required to automate this IZ localization procedure. The objective is to develop innovative methods for the multi-channel sEMG-based automatic localization of muscle IZs, specifically for the EAS muscle and broadly for other skeletal fusiform muscles.

II. RELATED WORK

Researchers have recently made numerous attempts at automating the process of localizing innervation zones in multi-channel surface electromyography (sEMG) [12] indicates that the electrode with the lowest sEMG RMS value is the one where the MU-IZs are located. This is not always the case, however, as in the case of EAS muscle, there are typically channels that have no MUAP activity but are nonetheless recognised as IZs since their RMS is likewise lower than that of the other channels. The method's other drawback is that it can only identify one IZ per epoch of the EMG signal because it computes the lowest EMG RMS over all channels for the whole epoch, which only has one value and can only identify one IZ. However, for EAS, the IZs are under distinct electrodes for various MUAPs, and the muscular MUs are typically not innervated at the same spot (see Fig. 3). Methods based on optical flow techniques were proposed by Östlund et al. in [13] and Saitou et al. in [14]. None of these techniques, however, were applied especially for the signal from the EAS muscle or compared to the ground truth value (the real position of IZ). There are also some more recent strategies based on multi-channel sEMG that use template matching and the Radon Transform [15], [16], however none of these systems extract the MU-IZ using a 2D spatio-temporal EMG map. The exceptionally accurate method for the automatic detection of motor unit IZs that we previously presented in [2] requires a preliminary decomposition of the EMG signal into individual motor unit action potentials, which is computationally expensive and cannot be completed in real-time. The authors of [17] employed a novel approach based on graph cut segmentation for the detection of IZs. This technique can identify several innervation zones, however, is only used to analyse synthetic data rather than complicated experimental EMG signals from EAS muscles. In a recent study in [18], the authors proposed a new method for innervation zone localization based on ICA and radon transform. Although the results of the proposed method are good for clean EMG signals, however the radon transform is very sensitive to noise. In order to detect many IZs in a single EMG epoch without first decomposing the signal, and from noisy signals, a novel approach for IZs localization needs to be devised. The proposed method overcomes these limitations with following contributions.

i. The proposed method detects muscle innervation zone directly from multi-channel EMG without prior decomposition of the signals.
ii. A novel representation as spatio-temporal image of the multi-channel EMG is proposed.
iii. For IZ localization a novel linearity measure in spatio-temporal EMG image is presented which detects innervation zones with high accuracy.

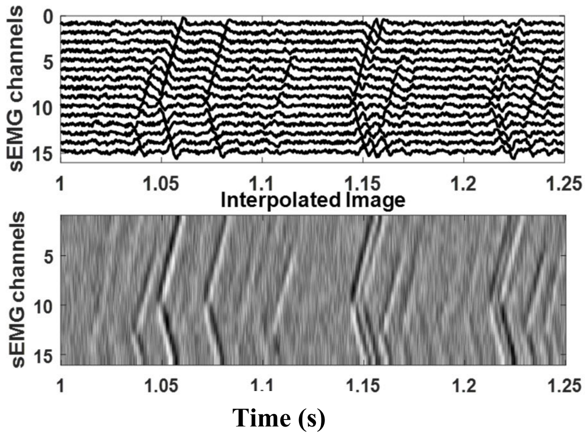


FIGURE 2. a) 15-channel simulated single differential noisy EMG signal, b) its corresponding interpolated spatio-temporal EMG image.

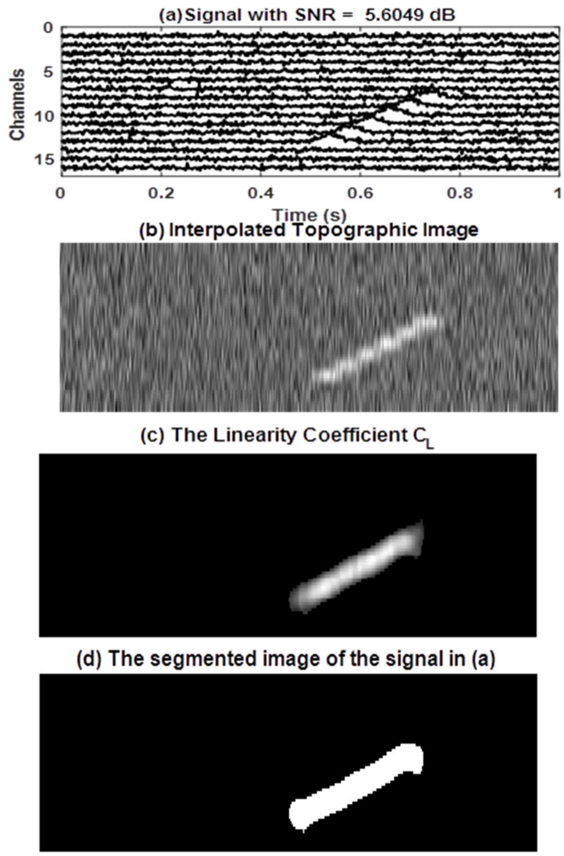


FIGURE 3. a) A synthetic 16 channel noisy signal with a propagating Gaussian profile, b) the corresponding spatio-temporal image, c) The linearity coefficient for the image in b). It is evident from the results that the tubular structure in the given image is enhanced while the background is suppressed. d) The segmented tubular region.

III. METHODS AND MATERIALS

Multi-channel sEMG signals can be represented using spatio-temporal images where time is depicted along the x-axis, electrode numbers along the y-axis, and EMG amplitude is the gray level of the image. An example of sEMG

TABLE 1. Local structure classification in image based on eigenvalues of Hessian matrix of each pixel in the image.

Type of structure in an image	Absolute First eigenvalue | $\lambda1$|	Absolute 2nd eigenvalue | $\lambda2$|
Background	Small	Small
Line-like MUAP structure	Small	Large
Spot	Large	Large

signal and its corresponding spatiotemporal EMG image are depicted in Figs. 2a and b, respectively. Over a grey background, the MUAP propagation pattern appears as a structure that resembles a series of, white, and black lines. Positive EMG amplitude causes the white pattern, while negative amplitude causes the dark pattern.

In a spatio-temporal sEMG image with a MUAP pattern, a Gaussian waveform can be used to mimic both the bright and dark regions [19]. So, a filter for MUAP representation, augmentation, and detection can be created using multi-scale second order local structure (Hessian). To do this, the local likelihood of the MUAP propagation pattern can be calculated using the Eigenvalues of the Hessian matrices for each pixel of the sEMG pictures. A similar approach is used by Ullah et al. to enhance linear features in digital images [19]. Based on the work of Farina and Merletti [20] we proposed a multi-scale method to detect MUAP propagation in sEMG images. The EMG spatio-temporal image is first convolved with the derivative of a Gaussian at various scales, and then essian matrix is computed for each pixel. The eigenvalues namely λ_1 and λ_2 of the Hessian matrix for each pixel are then computed to determine whether that pixel is a part of the MUAP propagation structure or not. It is discovered that a sEMG image pixel in a MUAP propagation region has λ_1 smaller (almost zero) and λ_2 negative and of greater magnitude [19]. To locate the local MUAP structure in the images, one can use these eigenvalues. Table 1 [20] lists the classification of local structures that can be determined based on eigenvalues of Hessian. This multi-scale technique enables the enhancement and detection of the linear structure i.e. MUAP in sEMG spatiotemporal images.

A. ELECTRODE ARRAY FOR sEMG ACQUISITION

Multi-channel sEMG signals are acquired from human muscles using a linear array of N equally spaced electrodes placed over a muscle along the direction of muscle fiber. Using this configuration N monopolar signals are acquired which are then converted to N-1 single differential sEMG signals. Such electrode arrays used in this study are developed, at LISiN politecnico di Torino, by Roberto Merletti and his team [21]. The signals acquired with this configuration are 1D signals for one electrode with respect to time. However for multiple electrodes the signals can be represented as 2D spatio-temporal image where the electrode covers the space and the time is the 2^{nd} dimension.

B. MUAP DETECTION USING EIGENVALUES OF THE HESSIAN

A pixel in the sEMG spatio-temporal image can be categorised as either belonging to the background, a line-like (MUAP) structure, or a spot based on the eigenvalues of the Hessian, as was previously mentioned, and summarised in Table 1. While the eigenvalues can categorise a pixel, they are unable to reveal any details regarding that pixel's intensity level. To quantify the line-like MUAP pattern in the spatiotemporal EMG images, we propose a metric called Linearity Coefficient (C_L), based on the eigenvalues of Hessian for each pixel, the following two variables are initially calculated: 1) the norm N and 2) the eigenvalues ratio R.

$$N = \sqrt{\lambda_1^2 + \lambda_2^2}, \quad R = \frac{|\lambda_1|}{|\lambda_2|} \tag{1}$$

The linearity coefficient is calculated using the Norm (N) and eigenvalues ratio (R) as follows.

$$C_L = N * (1 - R) \tag{2}$$

For a pixel belonging to the line-like MUAP propagation region, the value of N is higher as the absolute value of the 2nd eigenvalue ($|\lambda_2|$) is higher, while the ratio R is nearly zero as the first eigenvalue of λ_1 is zero and the 2nd eigenvalue λ_2 is higher thus C_L is nearly one. In contrast, for a pixel belong to the background region, R is nearly one and N is lower thus C_L is nearly zero. Thus the MUAP propagation region in the image after applying the linearity measure of equation 2, is enhanced and the background region with noise is suppressed as the C_L value is nearly one for the MUAP region and zero for the background. To elaborate the performance of the proposed linearity measure, an example of synthetic signal and its spatio-temporal image with a Gaussian profile of width $\sigma = 15$ pixels is synthetically simulated as shown in Fig. 3a and 3b respectively.The linearity coefficient C_L of this synthetic image is shown in Fig. 3c. It is clear from the Fig.3c that the C_L is higher for the tubular structure while zero for the background pixels. Thus this linearity coefficient is successfully suppressing the background noise while retaining the tubular line-like structure (similar to MUAP propagation) and enhances it in the image. The enhanced image can now be binarized using adoptive threshold. This threshold is chosen to be 0.07 in this study after empirical findings on several sets of EMG signals. The segmented tubular region for the synthetic signals of Fig. 3a is shown in Fig. 3d. An example of the linearity coefficient CL computed for a simulated EMG signal (simulated using the model presented in [22] is also shown in Fig. 4. The signal is contaminated with uniform noise of SNR 10dB. It can be seen from the results in Fig 4c that despite the presence of the noise, the linearity coefficient is High in the MUAP propagation region and is zero otherwise which leads to an enhanced image in which the MUAP propagation region is now clearly distinct from the background and can be segmented using an adaptive threshold or any other segmentation method. The segmented

TABLE 2. Interquartile range values, 95% confidence intervals, mean value and the p values (probability of observing the given result, by chance if the null hypothesis is true) for the error distributions of IZ identification comparing different methods.

		Simulated signals	Experimental signals
		vs Real IZ (IED)	vs Visual IZ (IED)
Linearity Measure based method	IQR:	0.1633	0.1748
	95%CI:	[-0.250 ÷ 0.148	[-0.128 ÷ 1.039]
	μ; p(μ≠0)	μ = -0.0051; p=0.32	μ = -0.0027; p=0.298
2DCorr	IQR:	0.23	0.32
	95%CI:	[-1.14 ÷ 1.06]	[-0.88 ÷ 1.09]
	μ; p(μ≠0)	μ = -0.013; p=0.057	μ = 0.007; p=0.07
Radon	IQR:	0.42	0.49
	95%CI:	[-0.84 ÷ 0.81]	[-0.90 ÷ 1.57]
	μ; p(μ≠0)	μ = -0.014; p=0.10	μ = 0.09; p<0.05
Templ. M.	IQR:	2.32	1.19
	95%CI:	[-1.97 ÷ 1.74]	[-2.38 ÷ 3.97]
	μ; p(μ≠0)	μ = -0.13; p=0.56	μ = -0.21; p<0.01

MUAP region after binarization using adaptive thresholding is shown in Fig 4c.

C. DETECTION OF THE IZs FROM THE MUAP SEGMENTED IMAGES

The MUAP segmented image has sometime some small non propagating region falsely identified due to noise in the sEMG signals. Thus, morphological operators like dilation and erosion are used to remove the outliers. As multiple firing of the same MU or firing of different MUs can occur in a single EMG epoch, thus multiple MUAPs are detected by the proposed method in a single EMG spatio-temporal image. Thus, labels are assigned to all the regions identified in the image. For each region then various parameters like starting and end points, slope of the central axis, y-intercept of the central axis etc. are computed. These parameters are used to group the regions belonging to same MUAP.

Each MUAP region is then classified as propagating in upward direction (upward Line) or downward direction (downward Line) based on their slope. Before identifying the IZs, we first determine either there is bidirectional or unidirectional MUAP propagation at a particular time instant. For this purpose, we compare the starting time instants of the upward and downward propagating lines. If the upward and downward propagating lines start at the same time instant and there is a difference of 1 channel (with some tolerance) between their starting channels, then bidirectional propagation is recorded and the point of intersection of the upward and downward propagating regions correspond to the IZ at that time instant. Otherwise, unidirectional propagation is recorded and the IZ is the starting of the upward or the downward propagating line (whichever exists at that time instant). An example of the proposed method applied to experimental EMG signals from EAS muscle is shown in Fig. 5.

IV. RESULTS AND DISCUSSION

As a result of various noises and the destructive interference of neighboring MUAPs, EMG spatio-temporal images have poor MUAP visibility. Due to a combination of destructive and constructive interferences, as well as the presence and

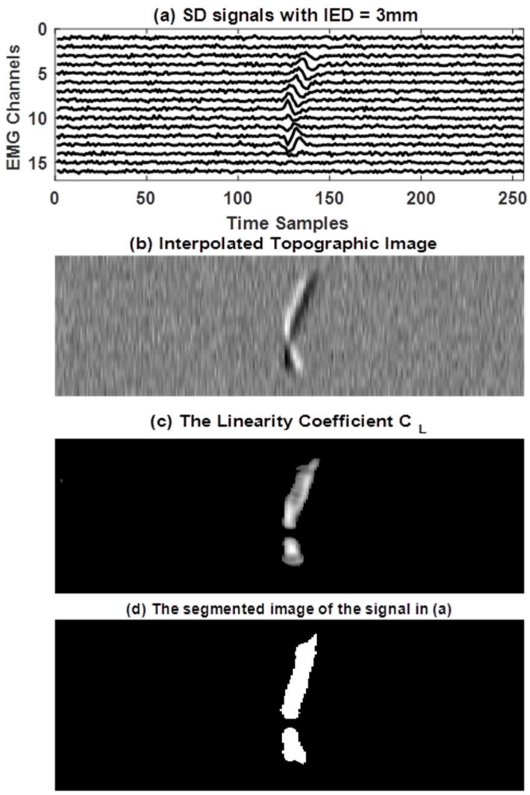


FIGURE 4. a) A 16 channel noisy simulated single differential EMG signal, b) Its corresponding interpolated spatio-temporal EMG image, c) The linearity coefficient for the image in b). It is evident from the results that the MUAP structure in the given image is enhanced while the background is suppressed. d) The segmented MUAP.

absence of noises at various electrodes, the thickness of the MUAP propagation region might occasionally be irregular [19]. Thus, a multi-scale fiter is required to reduce background noise while maintaining and enhancing the MUAP regions at various scales proportional to the MUAP width. This is achieved by computing the hessian matrix at different scales and then the linearity matrix is used for MUAP detection which leads to detection of MUAP of different sizes and widths.

To evaluate the performance of the proposed method, three types of signal datasets are used. The first dataset consists of synthetic images with gaussian propagating profiles of different width. An example of such synthetic image, the linearity measure, and the detected propagating structure (like MUAP) are shown in Fig. 3.

The 2nd dataset is a set of simulated EMG signal generated using the cylindrical model of the muscle proposed by Farina and Merletti [20]. The model takes a source which is a spatio-temporal function that characterised the creation, propagation, and extinction of the intracellular action potential at the end-plate, along the fibre, and at the tendons, respectively. The volume conductor was described as an anisotropic multi-layered cylinder. The Inter-Electrode-Distance (IED) was set to 5 mm and the rest of the model parameters were same as described in [2]. 16 Single Differential (SD) channels with a sampling frequency of 2048 samples/sec were simulated along the muscle fibre direction. An example of the simulated signal, the detected motor units using the linearity measure and the corresponding motor unit IZs are shown in Fig. 6. A total of 640 MUAPs were produced using the cylindrical model of [19] to compare the proposed method with the others mentioned in this paper. The model generates EMG signal with single MUAP recorded by a circumferential 16 electrode array in single differential mode. Single MUAP is generated because the methods discussed here are able to detect IZ of a single MUAP only. The proposed method is compared with 2D correlation method [2], Radon Transform method [15] and Template Matching method [16]. Error between the actual location and the detected location by each method is computed for these simulated signals. As for most of the methods the error distribution was not Gaussian so the median and interquartile range of the error are computed as performance indicators. For the simulated signals, the proposed linearity measure (LC) based method showed the least inter quartile ranger (IQR) error of 0.1633 IED compared to the 2DCorr with IQR of 0.2312 IED, Radon Transform 0.4926 IED and Template Matching 1.1926 IED.

Comparisons between the median of the error distributions were made using the Wilcoxon signed rank test. The comparison and error analysis in identification of innervation zone for simulated signals is summarized in Table 1. It is evident the proposed method outperform with least IQR error. The Template matching method uses a threshold whose optimal value is difficult to determine that is why it has higher error in IZ localization. Other drawbacks of the 2DCorr, Radon Transform and Template matching method is that it can only detect single IZ per epoch. However in most of the cases for EAS muscle there are multiple Innervation zones and the proposed linearity measure based method is able to detect multiple Innervation Zones per epoch. An example of such EMG signal with multiple motor units firing and multiple innervation zones is shown in Fig. 6. The average error of the proposed method for simulated signals for multiple channels is 0.53 IED.

The third dataset consists of experimental EMG signals captured from 150 patients chosen at random from a clinical study on External Anal Sphincter (EAS) muscle [21], [22], [23]. The probe shown in Fig. 7a was used to find the signals. Intra-anal sEMG signals were recorded at 2048 Hz, stored on a PC after 16 bit A/D conversion, and then bandpass filtered off-line in the frequency range of 20 to 450 Hz. The intra-anal sEMG signals were recorded in single differential mode using a 16 channel EMG amplifier (www.lisin.polito.it, Torino, Italy) with a gain of 186 V/V, 2-500 Hz 3 dB Each participant was instructed to unwind while the basic sEMG signal was captured for 10 seconds, and they then had to contract strongly while the EMG signal was likewise recorded for 10 seconds.

Figure 7b depicts an example of a sEMG signal from EAS muscle. Additionally shown in Fig. 7 are the associated interpolated spatio-temporal image, the segmented MUAP

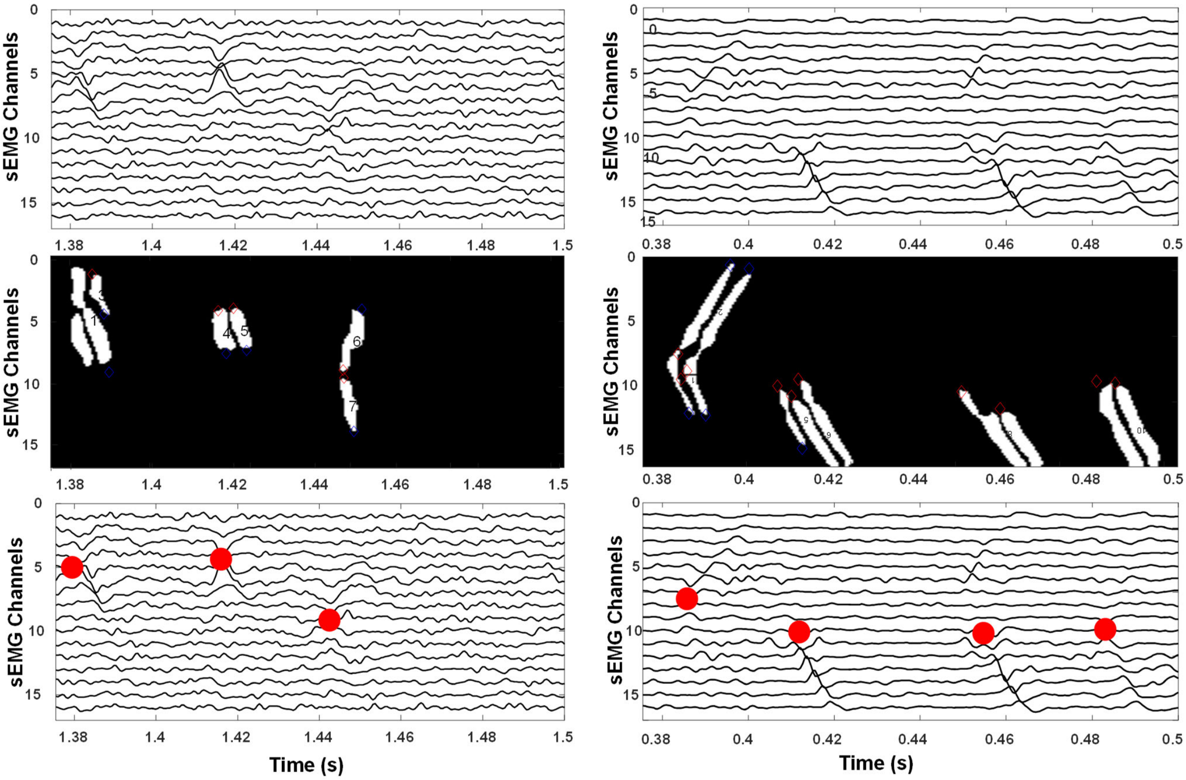


FIGURE 5. Example of EMG signals from EAS muscle of two subjects, the detected MUAPs and the detected IZs using the proposed method. The red spheres represent the location of the innervation zone.

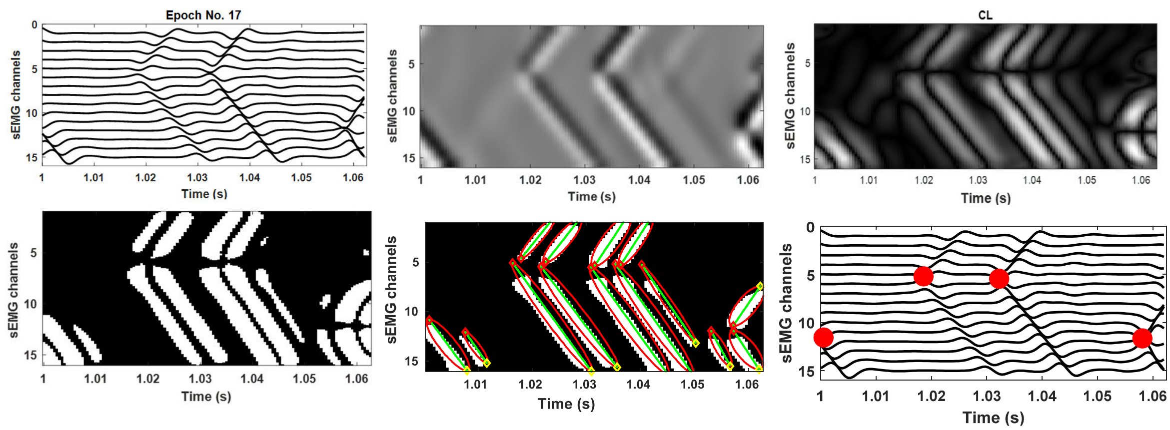


FIGURE 6. Simulated EMG signals, the spatio-temporal EMG image, the Linearity measure, the segmented MUAP, the grouped regions related to single MUAP, the detected Innervation Zones using the proposed method.

regions, the grouped regions, and the recognised Innervation zones. Using these experimental sEMG signals from EAS muscle, the suggested method was compared with the competing approaches. The innervation zones of the EAS muscle were found using these experimental EMG data using the proposed Linearity measure approach, which had the lowest IQR error of 0.1748 IED. The IQR error for the 2DCorr method was 0.32 IED, but the IQR errors for the RT and the TM were 0.49 IED and 1.19 IED, respectively. The detailed analysis is shown in Table 1. Since the true positions of the IZ were unknown, the inaccuracy was calculated in relation to the visual identification on interpolated signals (interpolation factor of 10). Since thresholds are applied by the TM and RT algorithms when identifying the IZ, in 31% of the cases, these approaches failed to do so. The TM technique additionally provides a bimodal distribution of the error. Since the position of the IZ in experimental signals is unknown and expert visual identification of the IZ is the gold standard.

In comparison to other approaches published in the literature, the unique method for MUAP detection and subsequent MU IZ localization shown in this study offers improved results, and it is in good agreement with the gold standard

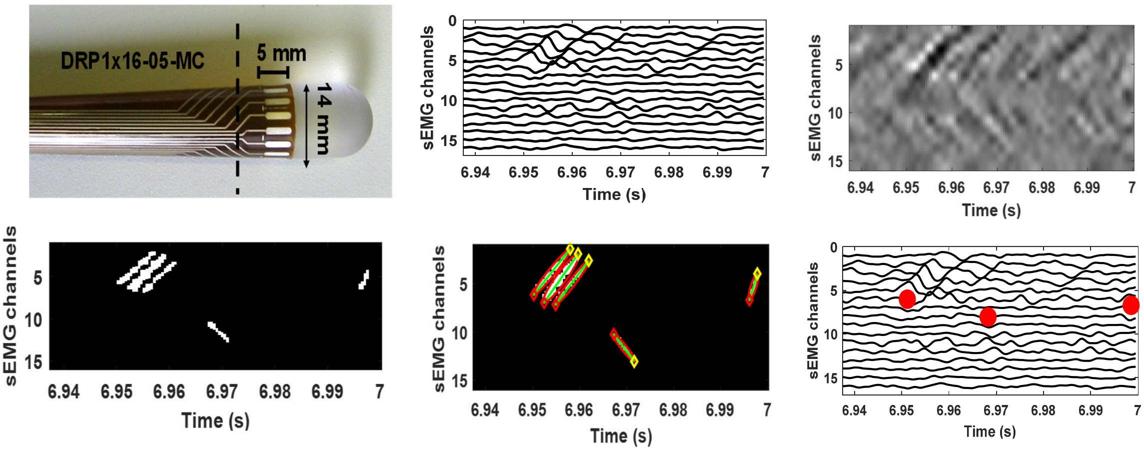


FIGURE 7. a) 16-channel probe for acquisition of sEMG signal from EAS muscle, b) Example of a 16-channel sEMG acquired using the electrode probe shown in a for 10m.

offered by the visual detection carried out by an expert operator (Fig. 7 and Table 1). The method has one minor drawback: It necessitates a certain number of non-overlapping MUAPs in a single epoch. Additionally, the method's small tails of inaccuracy are probably caused by motor units that are very close to one another and fire simultaneously. In contrast to the time-consuming visual analysis, which provides a median bias of 1.1 percent of IED, IQR = 0.20 IED, and 95 percent CI = [0.72 to 0.68], the proposed method is nearly bias-free, IQR = 0.17483 IED. The proposed linearity measure based technique might be used on any skeletal muscle, while being specifically designed for the sphincter muscles.

V. CONCLUSION

This research work presents a novel method for muscle innervation zones localization from spatio-temporal sEMG images. The method based on multi-scale filter has however overcome the limitations of the 2DCorr method as it does not require any prior decomposition of the EMG signal. In conclusion, a novel method for automatic IZ location was developed and tested on simulated and on experimental MUAP signals detected from the EAS. The performance of the method is comparable to that of an expert human operator. The method may further be improved by using suitable pre-processing techniques to enhance the quality of the images.

REFERENCES

[1] M. Barbero, R. Merletti, and A. Rainoldi, "Introduction and applications of surface EMG," in *Atlas of Muscle Innervation Zones*. Milan, Italy: Springer, 2012, pp. 3–6.

[2] K. Ullah, C. Cescon, B. Afsharipour, and R. Merletti, "Automatic detection of motor unit innervation zones of the external anal sphincter by multichannel surface EMG," *J. Electromyogr. Kinesiol.*, vol. 24, no. 6, pp. 860–867, Dec. 2014.

[3] A. Holtermann, P. J. Mork, L. L. Andersen, H. B. Olsen, and K. Sogaard, "The use of EMG biofeedback for learning of selective activation of intra-muscular parts within the serratus anterior muscle: A novel approach for rehabilitation of scapular muscle imbalance," *J Electromyogr Kinesiol*, vol. 20, no. 2, pp. 359–365, 2010.

[4] D. Staudenmann, I. Kingma, A. Daffertshofer, D. F. Stegeman, and J. H. van Dieen, "Improving EMG-based muscle force estimation by using a high-density EMG grid and principal component analysis," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 4, pp. 712–719, Mar. 2006.

[5] T. Rantalainen, A. Klodowski, and H. Piitulainen, "Effect of innervation zones in estimating biceps brachii force-EMG relationship during isometric contraction," *J. Electromyogr. Kinesiol.*, vol. 22, no. 1, pp. 80–87, Feb. 2012.

[6] D. N. Samarasekera, M. T. Bekhit, J. P. Preston, and C. T. M. Speakman, "Risk factors for anal sphincter disruption during child birth," *Langenbeck's Arch. Surg.*, vol. 394, no. 3, pp. 535–538, May 2009.

[7] C. Cescon, E. E. Raimondi, V. Zač esta, K. Drusany-Starič, K. Martsidis, and R. Merletti, "Characterization of the motor units of the external anal sphincter in pregnant women with multichannel surface EMG," *Int. Urogynecol. J.*, vol. 25, no. 8, pp. 1097–1103, Aug. 2014.

[8] C. Cescon, D. Riva, V. Zacesta, K. Drusany-Staric, K. Martsidis, O. Protsepko, K. Baessler, and R. Merletti, "Effect of vaginal delivery on the external anal sphincter muscle innervation pattern evaluated by multichannel surface EMG: Results of the multicentre study TASI-2," *Int. Urogynecology J.*, vol. 25, no. 11, pp. 1491–1499, Nov. 2014.

[9] M. Viswanathan, K. Hartmann, R. Palmieri, L. Lux, T. Swinson, K. N. Lohr, G. Gartlehner, and J. Thorp Jr., "The use of episiotomy in obstetrical care: A systematic review," Evidence Report/Technology Assessment (Prepared by the RTI-UNC Evidence-based Practice Center, Under Contract), Agency Healthcare Res. Qual., Rockville, MD, USA, Tech. Rep., 05-E009-2, May 2005.

[10] J. Wissel, A. Manack, and M. Brainin, "Toward an epidemiology of poststroke spasticity," *Neurology*, vol. 80, pp. 13–19, Jan. 2013.

[11] B. G. Lapatki, J. P. van Dijk, B. P. C. van de Warrenburg, and M. J. Zwarts, "Botulinum toxin has an increased effect when targeted toward the muscle's endplate zone: A high-density surface EMG guided study," *Clin. Neurophysiol.*, vol. 122, no. 8, pp. 1611–1616, Aug. 2011.

[12] A. Rainoldi, G. Melchiorri, and I. Caruso, "A method for positioning electrodes during surface EMG recordings in lower limb muscles," *J. Neurosci. Methods*, vol. 134, no. 1, pp. 37–43, Mar. 2004.

[13] N. Östlund, B. Gerdle, and J. Stefan Karlsson, "Location of innervation zone determined with multichannel surface electromyography using an optical flow technique," *J. Electromyogr. Kinesiol.*, vol. 17, no. 5, pp. 549–555, Oct. 2007.

[14] K. Saitou, T. Masuda, D. Michikami, R. Kojima, and M. Okada, "Innervation zones of the upper and lower limb muscles estimated by using multichannel surface EMG," *J. Hum. Ergol.*, vol. 29, no. 1, pp. 35–52, 2000.

[15] C. Cescon, "Automatic location of muscle innervation zones from multi-channel surface EMG signals," in *Proc. IEEE Int. Workshop Med. Meas. Appl.*, Benevento, Italy, Apr. 2006, pp. 87–90, doi: 10.1109/MEMEA.2006.1644467.

[16] L. Mesin, M. Gazzoni, and R. Merletti, "Automatic localisation of innervation zones: A simulation study of the external anal sphincter," *J. Electromyogr. Kinesiol.*, vol. 19, no. 6, pp. 413–421, Dec. 2009.

[17] H. R. Marateb, M. Farahi, M. Rojas, M. A. Mañanas, and D. Farina, "Detection of multiple innervation zones from multi-channel surface EMG recordings with low signal-to-noise ratio using graph-cut segmentation," *PLoS ONE*, vol. 11, no. 12, Dec. 15, 2016, Art. no. e0167954, doi: 10.1371/journal.pone.0167954.

[18] C. Huang, Z. Lu, M. Chen, C. S. Klein, Y. Zhang, S. Li, and P. Zhou, "Muscle innervation zone estimation from monopolar high-density M-waves using principal component analysis and radon transform," *Frontiers Physiol.*, vol. 14, Mar. 2023, Art. no. 1137146.

[19] K. Ullah, K. Khan, M. Amin, M. Attique, T.-S. Chung, and R. Riaz, "Multi-channel surface EMG spatio-temporal image enhancement using multi-scale hessian-based filters," *Appl. Sci.*, vol. 10, no. 15, p. 5099, Jul. 2020, doi: 10.3390/app10155099.

[20] D. Farina and R. Merletti, "A novel approach for precise simulation of the EMG signal detected by surface electrodes," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 6, pp. 637–646, Jun. 2001.

[21] R. Merletti and S. Muceli, "Tutorial. Surface EMG detection in space and time: Best practices," *J. Electromyogr. Kinesiol.*, vol. 49, Dec. 2019, Art. no. 102363.

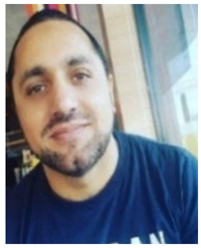
[22] B. M. Wietek, H. Hinninghofen, E. C. Jehle, P. Enck, and H. B. Franz, "Asymmetric sphincter innervation is associated with fecal incontinence after anal sphincter trauma during childbirth," *Neurourol. Urodynamics*, vol. 26, no. 1, pp. 134–139, Jan. 2007.

[23] P. Enck, H. Hinninghofen, R. Merletti, and F. Azpiroz, "The external anal sphincter and the role of surface electromyography," *Neurogastroenterol. Motility*, vol. 17, no. 1, pp. 60–67, Jun. 2005.

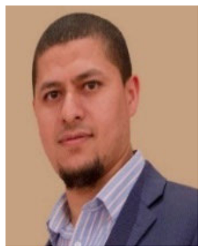
KHALIL ULLAH received the degree in computer systems engineering from the University of Engineering and Technology, Peshawar, Pakistan, in 2006, the Master of Science (M.S.) degree in electronics and communications engineering from Myongji University, South Korea, in 2009, and the Ph.D. degree in biomedical engineering from LISiN, Politecnico di Torino, in 2016, under the Erasmus Mundus Expert II Fellowship. He is currently acting as an Assistant Professor and the Head of the Software Engineering Department, University of Malakand. His research interests include extracting muscle anatomical and physiological information from high-density electromyography, computer vision, digital signal and image processing, and deep learning with applications to medical healthcare, the IoT, and NLP.

SULAIMAN ALMUTAIRI received the bachelor's degree in computer science from Bluefield State University, USA, the master's degree in information technology from RMU, USA, and the Ph.D. degree in biomedical informatics from Rutgers University, NJ, USA. He has been a Tenure with Qassim University, since 2005. He has held various pivotal roles, including the Vice Dean of Planning, Development, and Quality. He is currently a Distinguished Data Governance Consultant and the Director of quality scholarship services of the Ministry of Education. He also holds the position of an Assistant Professor of health informatics with Qassim University. He has showcased his expertise as a Data Governance Consultant with prominent tech firms in Saudi Arabia, such as Elm and SITE. Additionally, he served as a cultural mission diplomat representing Saudi Arabia in Canada and contributed globally as a Data Consultant with Development Gateway and UNICEF. His areas of expertise encompass data governance, bio-informatics, information and policy, and software development.

RIAZ AHMAD received the M.S. degree (Hons.) in computer science from NUCES (FAST) University, Pakistan, in 2010, and the Ph.D. degree from the Technical University of Kaiserslautern, Germany, in 2018. He was a member with the Multimedia Analysis and Data Mining (MADM) Research Group, German Research Center for Artificial Intelligence (DFKI), Kaiserslautern, Germany. Currently, he is the Head of the Computer Science Department, Shaheed Benazir Bhutto University Sheringal, Pakistan. His areas of research interests include document image analysis, image processing, and optical character recognition. More specifically, his work examines the challenges posed by cursive script languages in the field of OCR systems. In addition to that, he is studying the behavior of deep learning architectures in the field of OCR in terms of invariant approaches against scale and rotation variation in Pashto cursive text. During the M.S. degree, he secured top position in his batch.



SIRAJ MUHAMMAD received the M.Phil. degree from Quaid-i-Azam University, Islamabad, Pakistan, in 2010, and the Ph.D. degree from Asian Institute of Technology (AIT), Thailand, in 2020. He was a Software Engineer with Elixir Technologies, Islamabad, from 2010 to 2011. Currently, he is an Assistant Professor with the Department of Computer Science, Shaheed Benazir Bhutto University Sheringal, Pakistan. His research interests include reverse engineering, computer vision, image processing, deep learning, and natural language processing.



ABDALLAH NAMOUN (Member, IEEE) received the bachelor's degree in computer science, in 2004, and the Ph.D. degree in informatics from The University of Manchester, U.K., in 2009. He is currently a Full Professor of intelligent interactive systems and the Head of the Information Technology Department, Faculty of Computer and Information Systems, Islamic University of Madinah. He has authored more than 85 publications in research areas spanning intelligent systems, human–computer interaction, machine learning, smart cities, and technology acceptance and adoption. He has extensive experience in leading complex research projects (worth more than 23 million Euros) with several distinguished European SMEs, such as SAP, BT, and ATOS. His recent research interests include the integration of state-of-the-art artificial intelligence models in the development of interactive systems and smart spaces.

ISA ALI IBRAHIM was the Chief Digital Officer in Nigeria and the Cabinet Minister of communications and digital economy in Nigeria, from 2019 to 2023. He was appointed by the United Nations through ITU to serve as the Chairperson of more than 194 global ministers of ICT through WSIS 2022. He has been a Full Professor of cybersecurity with the Federal University of Technology Owerri, since March 2021, where he teaches pro-bono. He is currently the Chancellor of a public university in Sudan. He is a Governing Council Member with two universities. He authored more than ten books on emerging technologies and among others, published more than 35 journal articles, and attended more than 190 conferences as the keynote speaker, a presenter, or a discussant in more than 40 countries globally. He is a FCIIS, a FBCS, and a FNCS.