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REVIEW

Review on electromyography signal acquisition and processing

Vidhi Gohel[1] · **Ninad Mehendale**[1]

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Abstract

Electromyography (EMG) is a technique for recording biomedical electrical signals obtained from the neuromuscular activities. These signals are used to monitor medical abnormalities and activation levels, and also to analyze the biomechanics of any animal movements. In this article, we provide a short review of EMG signal acquisition and processing techniques. The average efficiency of capture of EMG signals with current technologies is around 70%. Once the signal is captured, signal processing algorithms then determine the recognition accuracy, with which signals are decoded for their corresponding purpose (e.g., moving robotic arm, speech recognition, gait analysis). The recognition accuracy can go as high as 99.8%. The accuracy with which the EMG signal is decoded has already crossed 99%, and with improvements in deep learning technology, there is a large scope for improvement in the design hardware that can efficiently capture EMG signals.

Keywords EMG · Electromyogram · sEMG

Introduction

The electrical activities generated by skeletal muscles represent the core EMG signal. EMG is used to read myoelectric signals via electrical measurements. These myoelectric signals are generated from motor neurons which are a part of the central nervous system (CNS). As EMG signals are due to neuromuscular activity, they can be used to diagnose muscle injury, nerve damage, and muscle dysfunction that happens due to neurological and muscular disorder. EMG signals are used to gather simple statistics or can be even used with advanced deep learning to control complex robotic applications (Fig. 1a). Furthermore, in some cases, EMG signals can be used for gait analysis and capturing muscle movements. Figure 2b shows the basic temporal characteristics of the EMG signal. The amplitude is the positive peak to negative peak voltage. Phase is the time duration of the initial negative cycle. The rise time is defined as the time interval between negative and positive peaks. There are three turns in the EMG signal. The duration is defined as the total time between two negative cycles. A satellite is a small signal followed by the main EMG signal.

There are two major types of electrodes used to measure EMG signals—the needle electrode and the surface electrode. Needle electrodes (Fig. 1c) are further classified into three subtypes: mono-polar single electrodes, single-fiber EMG electrodes, and concentric-EMG electrodes. Needle electrodes are approximately 1 mm^2 wide. Surface electrodes (Fig. 1d) are 0.5–2.5-cm wide and due to their positioning are non-invasive (Merlo et al. 2003). Surface electrodes work on the principle of chemical equilibrium detecting the change between the muscle surface and body skin through electrolytic conduction. Surface electrodes are of two types: gelled EMG electrodes and dry EMG electrodes.

There are 3 main types of electrograms, viz. electroencephalogram (EEG), electrocardiogram (ECG), and EMG. The advantage of using EMG over ECG and EEG is that ECG and EEG signals are below 100 Hz whereas EMG signals cover the range from 5 Hz to 2 kHz. EMG signals appear in different patterns and are difficult to understand. In this review paper, we explain how the different types of EMG signals are acquired and processed. This paper will be useful for medical and engineering communities for developing better diagnostics using EMG.

Speech recognition based on EMG signal

Many researchers have used EMG for speech recognition (Fig. 1b). Achieved recognition rates lie between 68 and

✉ Ninad Mehendale
ninad@somaiya.edu

[1] K. J. Somaiya College of Engineering, Mumbai, India

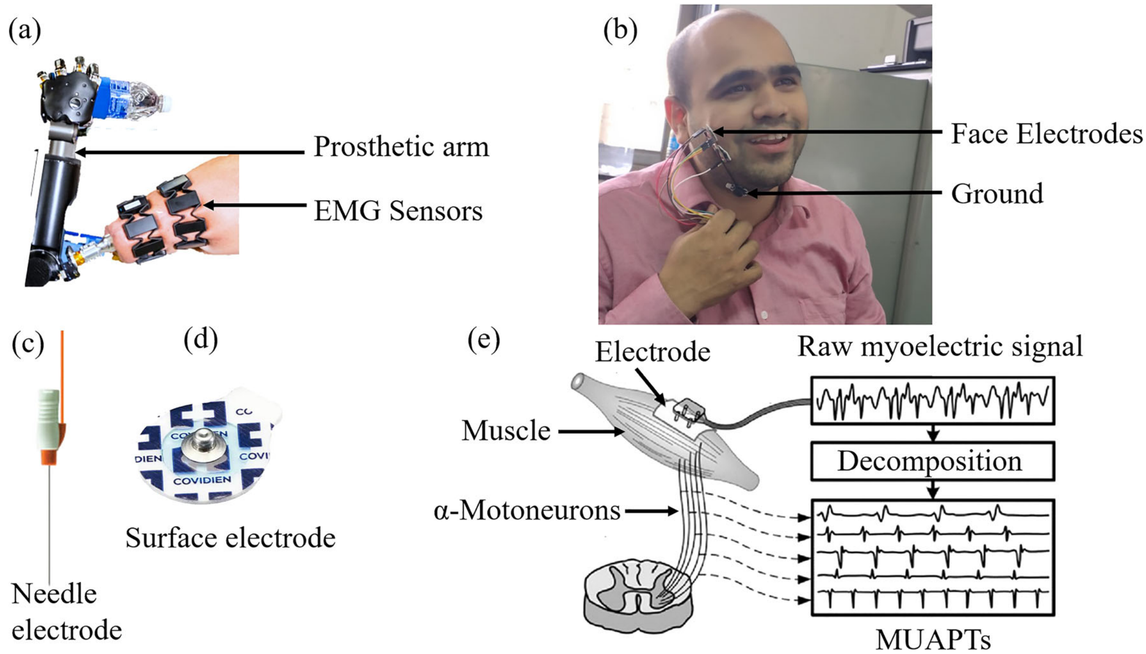

Fig. 1 Different EMG sensor electrode positions on the human body. **a** EMG sensor placed on biceps to move prosthetic arm. **b** EMG signal placed on the surface of human cheek for speech recognition **c** Needle electrode. **d** Surface electrode. **e** A schematic representation for the decomposition of the myoelectric signal (De Luca et al. 2006). It shows how motor unit action potential trains (MUAPTs are generated)

97% with an average success rate of 85.4% (Jorgensen et al. 2003). Recently, Meltzner et al. (2011) have developed an innovative method of speech recognition using EMG signals from the face. They used signal acquisition and processing techniques (Hershler and Milner 1978) on surface EMG (sEMG) (Khushaba et al. 2012). Traditionally, microphones are used for speech recognition, but the removal of surrounding noise is the major task. As an alternative, EMG sensors can now be used for speech recognition. People who can not speak can even convey the message through a computerized voice using this EMG method. They have achieved 92.1% accuracy. Figure 4a shows different sEMG sensor locations. Sensors 1 and 2 shows submental neck, sensors 3 and 4 show ventromedial

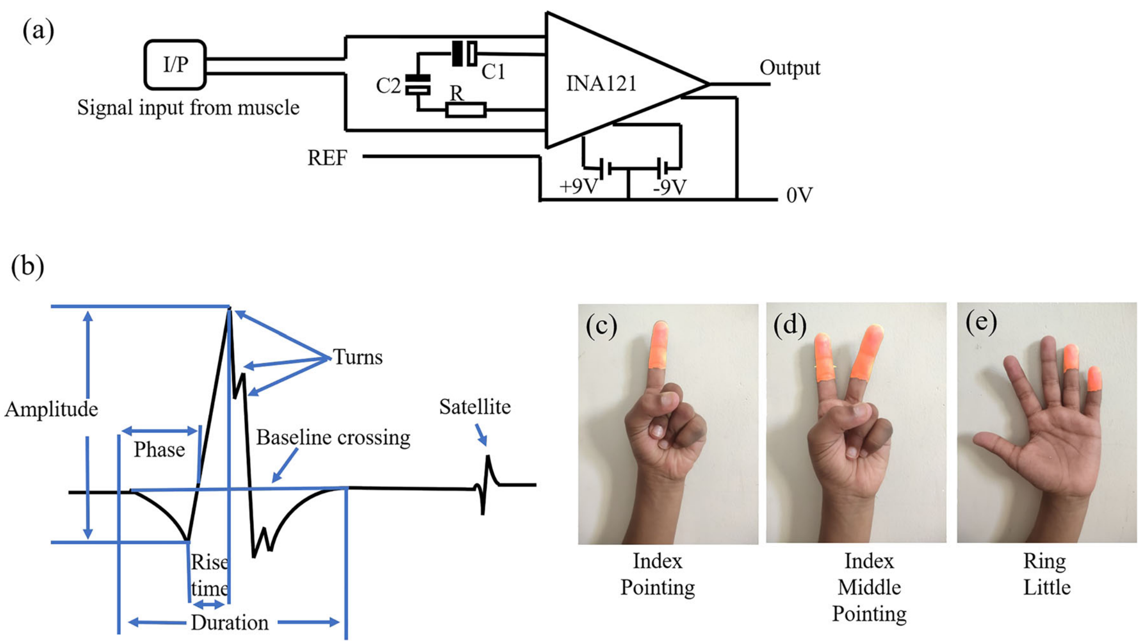

Fig. 2 **a** EMG amplifier circuit with DC coupling. **b** Temporal characteristics of EMG signal. Different positions of fingers while the hand is on the steering wheel, e.g., index finger open (**c**), index and middle finger open (**d**), the ring and little fingers open (**e**)

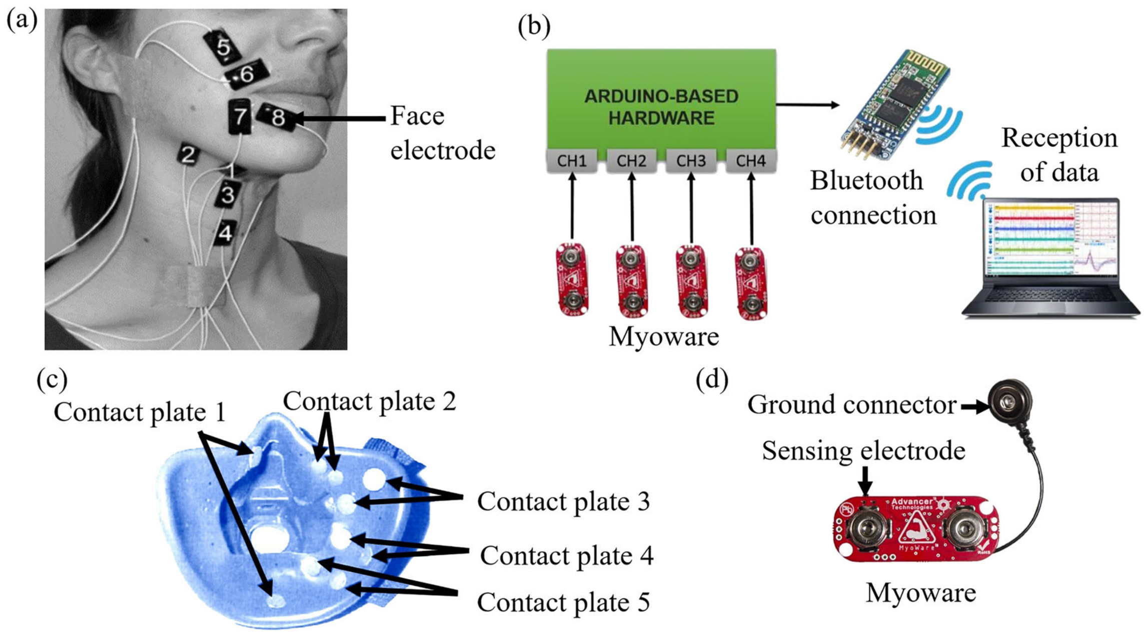

Fig. 3 **a** Different positions on the face, where electrodes should be placed to acquire proper EMG signal. **b** Portable EMG reader. Multiple MyoWare connected to Arduino and HC05 is used to transfer the data. **c** Face plate with electrodes for speech recognition. **d** MyoWare sensor

neck, sensors 5 and 6 show supralabial face position, and infralabial face placement is indicated by 7 and 8. Chan et al. (2001) have worked on the myoelectric signals (Fig. 4c) to augment speech recognition (ASR) with an accuracy of 93%. Jou et al. (2006) have worked on articulatory feature classification using sEMG achieving an accuracy of 68%. Lee (2008), in his research of EMG-based speech recognition using hidden Markov models with global control variables, achieved an accuracy of 87%.

Robotic applications based on EMG signal

EMG signals are often used as input in a lot of robotic applications (Osu and Gomi 1999; Wang and Buchanan 2002). Khan et al. (2012) have developed a portable EMG circuit for a prosthetic arm. This can be worn on both arms wherever necessary. The portable EMG circuit has achieved a high fidelity and excellent signal to noise ratio (Kiguchi et al. 2004). Figure 2a shows the dc-coupled amplification circuit that was employed by the group of Khan et al. It used IC 121 with a gain of 417 to the signal that was acquired from surface EMG electrodes. The input signal is directly connected between pins 2 and 3 without any coupling. Filtering capacitors and resistors are connected between pin 1 and pin 8. C1 and C2 have a value of 100 µF and the resistance (R) is 120 Ω. INA121 IC requires a 9-V DC supply connected between pins 7 and 4. The output is collected across pin 6 and reference pin 5. Samarawickrama et al. have analyzed the sEMG w.r.t upper limb and flexion angle (Samarawickrama et al. 2018). They used an INA128 amplifier and a UAF42 filter IC to classify the signals for the operation of prosthetic limbs. Jamal (2012) described signal acquisition using surface EMG (Nawab et al. 2010) and circuit design considerations for robotic prosthesis (Zecca et al. 2002). They explained all the different types of electrodes used in EMG signal analysis and described how to correctly place them to get an accurate EMG signal. In further work, the following electrodes were explained in detail—a needle electrode, a fine wire electrode, and a surface EMG electrode (Wang et al. 2013).

Diagnostics applications based on EMG signal

Pauk (2008) described different techniques for EMG signal processing. In that work, functional evaluation of 20 patients having spastic diplegia was carried out. Spastic diplegia is a form of cerebral palsy (CP) that displays chronic neuromuscular conditions of hypertonia and spasticity. The demographic data received was studied carefully and a raw EMG data was made. Witman et al. (2019) have explained the methods to get EMG signals and analyze it for finger movement. They used the MyoWare device with an ATmega 329P microcontroller (Fig. 3d). Finger movements were classified into 5 types and the acquired signals were transmitted using Bluetooth. For classification, they have used K-nearest neighbors (K-nn) method (Witman et al. 2019). They achieved an accuracy of 99.1% for

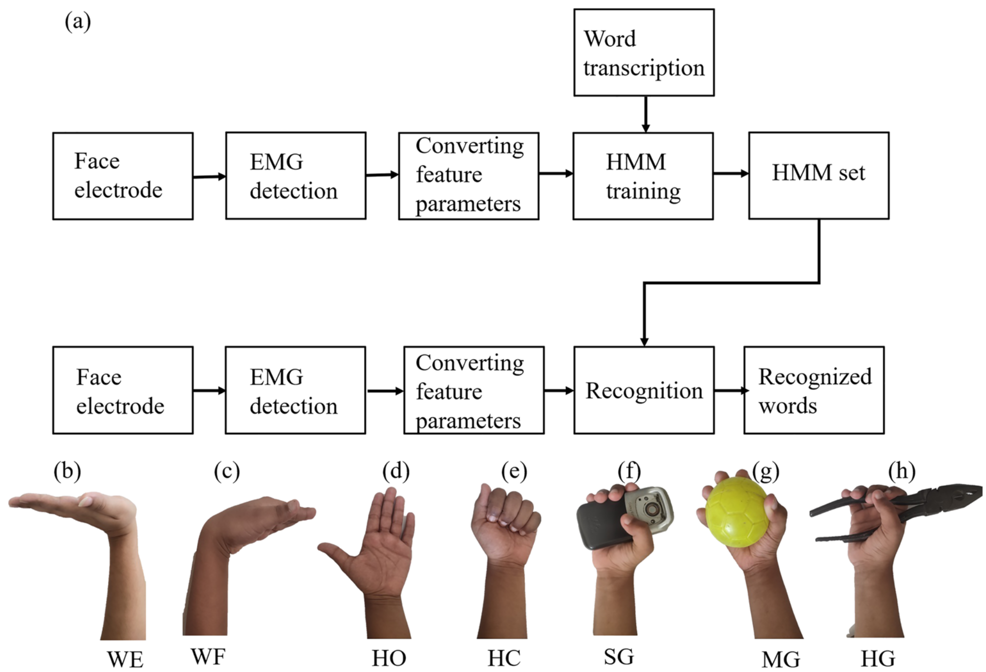

Fig. 4 **a** Block diagram of EMG-based automatic speech recognition (ASR) system. The upper of block diagram shows the offline (training) procedure. The lower part of the block diagram shows an online (recognition) procedure. Various arm positions: **b** wrist extension, **c** wrist flexion, **d** hand open, **e** hand close, **f** soft gripping, **g** medium gripping, **h** hard gripping

finger movement. Figure 4b shows how electrodes were placed into the channel slots to ensure that they were fixed properly and would not move. The Bluetooth connection was used, for data transmission from EMG hardware, and received using a computer. Di Nardo et al. (2014) developed a statistical analysis tool for EMG signal acquired from the tibialis anterior (TA) during gait. During acceleration, deceleration, and changes in the direction, a pattern was acquired. They found that about 20% of the total strides were TA active using the EMG signal.

EMG signal acquisition and processing

Pancholi and Agarwal (2016) have developed a low-cost EMG system for the acquisition of Arm Activities Recognition (AAR). They found that about 80% of the EMG signals were captured efficiently and the overall accuracy for AAR was about 79%. The EMG data can be collected from various upper limb actions, viz. HO (hand open), HC (hand closed), WE (wrist extension), WF (wrist flexion), SG (soft gripping), MG (medium gripping), and HG (hard gripping) as shown in Fig. 4b–h. Reaz et al. (2006) presented work on various obstacles (e.g., noise) that can interrupt EMG signal acquisition. They also explained means for their detection and means for classifying them into various forms. Shiavi and Negin (1973) found that about 1% of the detection of motor unit firing is difficult to capture in EMG signals, especially with wearable devices. Pizzolato et al. (2017) have compared multiple EMG acquisition setups of hand movement achieving an acquisition efficiency of 54%. Mambrito and De Luca (1984, 1983) have described a system for acquiring, processing, and also decomposing EMG signal to extract as many motor unit action potential (MUAPs) as possible with the accuracy of 99.8% (Fig. 1e). Khushaba et al. (2013) have developed machine-muscle computer interfaces for driver distraction reduction. In this work, they found the word error rate to be 7%. They proved EMG signals are used to analyze driver drowsiness and performance. The way the driver keeps the fingers on steering reflects how concentrated the driver is while driving. Figure 2c, d, and e show different classifications of recorded finger pressure (Myers et al. 2003).

These positions are typical driver's finger positions occurring when the driver's hand is kept on the steering wheel. Figure 2c shows the index finger open. Figure 2d shows the index and middle fingers open and (e) shows the ring and little fingers open.

Gijsberts et al. (2014) have developed novel methods for recording movement error rate for the evaluation of machine learning methods. These methods were tested on sEMG-based hand movement signal classifications and it was found that the effectiveness of signal capture was around 60% with the accuracy of signal recognition at about 82%. Milosevic et al. (2017) presented work regarding challenges related to design issues such as electrodes and complexity relating to constraints of signal processing. They tested EMG signal recognition with 3 datasets (viz. NINAPRO, UNIBO, Cerebro). They recorded an accuracy of 76.3% for

NINAPRO (all), 89.8% for NINAPRO (reduced), 88.9% for UNIBO, and 89.2% for Cerebro.

Mukhopadhyay and Samui (2020) had an experimental study based on the deep neural network in this work. They showed EMG signal can be used for obtaining the classification of a normal person from a person suffering from a neuromuscular disorder. Phinyomark et al. (2020) described the sEMG signal processing and pattern recognition techniques. They even described the various challenges faced in obtaining the signals. They classified EMGs into hands-free control and hands-busy control signals. Furthermore, their study involved different classification models and concluded with future directions. Fang et al. (2020) described the pattern recognition procedure and classification and even explained the challenges, such as low data quality, inadequate and undisclosed data, and discrete interpretation of continuous movements, faced by the researchers. Finally, their work concluded with analysis and future development and rectification to be made. Laryngeal EMG is a technique used to differentiate neurogenic from myogenic disorder. Lin and Robinson (2020) described laryngeal electromyography (LEMG) procedures and clinical applications; they even added LEMG techniques, components, and interpretation of the signals.

Analysis and discussion

For the purposes of this review, we recorded the capture efficiency, error rate, classification accuracy, type of electrode and recognition accuracy of multiple published papers (Khezri and Jahed 2007). Recognition accuracy is defined as the ability to correctly classify (Güler and Koçer 2005) the action by EMG signal decoding, while EMG capture efficiency is defined by the ability to accurately capture the EMG signals with respect to a standard electromyogram. Per Table 1, we found that the recognition accuracy ranges from 68 to 99.8%. For the majority of recorded literature, we found that recognition accuracy was more than 90%. Hence, there is a slight scope for improvement in recognition accuracy. The capture efficiency for EMG signals is considerably lower lying in the range of 50 to 80%. Hence, there is a large scope of improvement in designing proper EMG signal acquisition hardware with minimal noise.

Design guidelines for EMG system

1. For portable EMG systems, MyoWare is the best sensor available in the market. For accurate results, MyoWare sensors are preferred over low-cost sensors. Filters and rectifiers need to be added before amplification if MyoWare is not used.
2. Needle electrodes give equivalent accuracy to the surface electrodes; hence, the user should always go for a surface electrode-type EMG reader. As needle electrodes are invasive, the use of a surface electrode avoids pain caused by needle insertion. Also, the chance of contaminating blood due to needle insertion is also avoided.
3. One can also take the EMG signals while bending the finger to find the sensitivity of the system. But before placing the sEMG on the surface of the skin, keep in mind to remove the makeup properly with alcohol as well as clean the recording site.
4. Speech recognition is both precise and convenient when recorded by EMG for the deaf and dumb person. The surface electrodes must be placed on the chin and cheek of the person.
5. To acquire the EMG signal of limbs, the most suitable place is to take the signal from the back muscle, i.e., behind the tibia bone. In case the electrodes cannot be placed on the back muscle, then the next best location is the shoulders.
6. Wearable EMG can even be used for the detection of facial expressions. (The wearable part is placed from the back of the head touching the skin on the cheeks.)
7. sEMG sensors placed on the body parts such as the hips, elbows, and collar bones show more accurate results.
8. To reduce the electrical noise from the surroundings, keep the cable wires as short as possible.

Future directions

The sensitivity and quality of the EMG signal can be improved by using high-density EMG. Even a single-cell EMG signal detection would be possible in the near future due to advancements in VLSI technology, so we should be able to detect the fine movements rather than taking signals from the entire muscle tissue. More advanced algorithms and open-source databases with high data quality and accuracy can be used to solve the problem of pattern recognition, so that this attracts more researchers to join the field of EMG signal analysis for human behavior studies (Fang et al. 2020). Another problem to be solved is the removal of surrounding noise during signal processing, when the noise is large, i.e., low SNR, a visual inspection can be used to acquire the signals initially. Whenever the signal quantity is high, i.e., high SNR, the contaminants cannot affect the readings, so that the amplifiers can be used (Phinyomark et al. 2020).

Table 1 Comparison of different EMG systems with respect to the efficiency of EMG capture, error rate, classification accuracy, type of electrode, and accuracy of recognition

	Recognition accuracy	Capture efficiency	Error rate	Classification accuracy	Type of electrode
Meltzner et al. (2011)	92.1		7.9		Surface
Gijsberts et al. (2014)	82	60			Surface
Atzori et al. (2013)		70			
Chan et al. (2001)	93		7		
Bett and Jorgensen (2005)	74		26		
Jou et al. (2006)	68		32		Surface
Lee (2008)	87		13		
Pizzolato et al. (2017)		54			
Benatti et al. (2014)	89.2		10.8		
Milosevic et al. (2017)	89.8		10.2		
Shiavi and Negin (1973)	99				
Mambrito and De Luca (1984)	99.8		0.2		
Pancholi and Agarwal (2016)	78.85	80			Surface
Witman et al. (2019)	99.1		0.9		
Khushaba et al. (2013)	93		7		
Wang et al. (2013)			15.66		
Phinyomark et al. (2020)	68		32	Below 90	
Mukhopadhyay and Samui (2020)			6.52		
Fang et al. (2020)	90.85		9.15	37.85	
Giannoccaro et al. (2020)	80		20		Single-fiber needle
Aghaei-Lasboo et al. (2020)				90	Concentric needle

Conclusion

EMG signals are widely used in robotics to develop prosthetic arms and legs. They are also widely used in speech recognition. This literature review has demonstrated that useful EMG signals can be read through non-invasive surface electrodes; hence, it is highly recommended to use surface electrodes over traditional needle electrodes. Noise is still a big issue affecting the capture efficiency of the EMG signal. However with proper filtering, the captured signal can improve up to 40 dB. Machine learning and deep learning approaches in EMG signal analysis represent the next step that can take recognition accuracy more than 99%. For EMG signals in medical analysis applications, athletes and trainers can use EMG as a suitable feedback signal and the level of coaching can be taken to a whole different level. EMG is perhaps the most important and easy to capture biomedical signal, and a lot of patients with a disability can profit from its acquisition and recognition.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Involvement of human participant and animals This article does not contain any studies with animals or humans performed by any of the authors. All the necessary permissions were obtained from the Institute's Ethical Committee and concerned authorities.

Information about informed consent No informed consent was required as the studies do not involve any human participant.

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