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Review on Electromyography signal acquisition and processing.

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Abstract Electromyography (EMG) signal is the type of biomedical signal, which is obtained from the neuromuscular activities. Typically, an electromyogram instrument is used to capture the EMG signals. These signals are used to monitor medical abnormalities, activation level, and also to analyze the biomechanics of any animal movements. In this current work, we provide a short review of EMG signal acquisition and processing techniques. We found that the average efficiency to capture EMG signals with the current technologies is around 70 %. Once the signal is captured, the signal processing algorithms applied decides the recognition accuracy, with which signals are decoded for their corresponding purpose (e.g. moving robotic arm, speech recognition, gait analysis, etc). 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 the upcoming deep learning technology, there is a scope of improvement to design hardware, that can efficiently capture EMG signals.

Keywords EMG · Electromyogram · sEMG

1 Introduction

Electrical activities and skeletal muscles represent EMG signals. 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). EMG signal is due to neuromuscular activity and hence used to diagnosed muscle injury, nerve-damage, motor dysfunctioning 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. 1 (a)). Further, in some cases, EMG signals are used for gait analysis and capturing muscle movements. Fig 2 (b) shows temporal characteristics of EMG signal. The amplitude is the positive peak to negative peak voltage. Phase is the time duration of the initial negative cycle. Rise time is defined as the time required by a negative and positive peak. There are 3 turns in the EMG signal. Duration is defined as the total time between two negative cycles. Satellite is a small signal followed by the main EMG signal.

Majorly 2 types of electrodes used to measure these EMG signals which are needle electrode and surface electrode. Needle electrodes (fig. 1 (c)) are further classified into 3 types: mono-polar single electrodes, single-fiber EMG electrodes and concentric-EMG. Needle electrodes are approximately 1 sq. mm wide. On the other hand, Surface electrodes (fig. 1 (d)) are 0.5-2.5 cm wide. However, surface electrodes are non-invasive technology to measure and capture the EMG signals [2]. Surface electrodes work on the principle of chemical equilibrium detecting the change between surface and skin of the body through electrolytic conduction. Surface electrodes are of two types: gelled EMG electrode and dry EMG electrode.

There are 3 main types of electrograms, viz. electroencephalogram (EEG), electrocardiogram (ECG) and EMG. The advantage to use EMG over ECG and EEG is that: ECG and EEG signals are below 100 Hz whereas EMG signals are 5 Hz to 2 kHz. These EMG signals ap-

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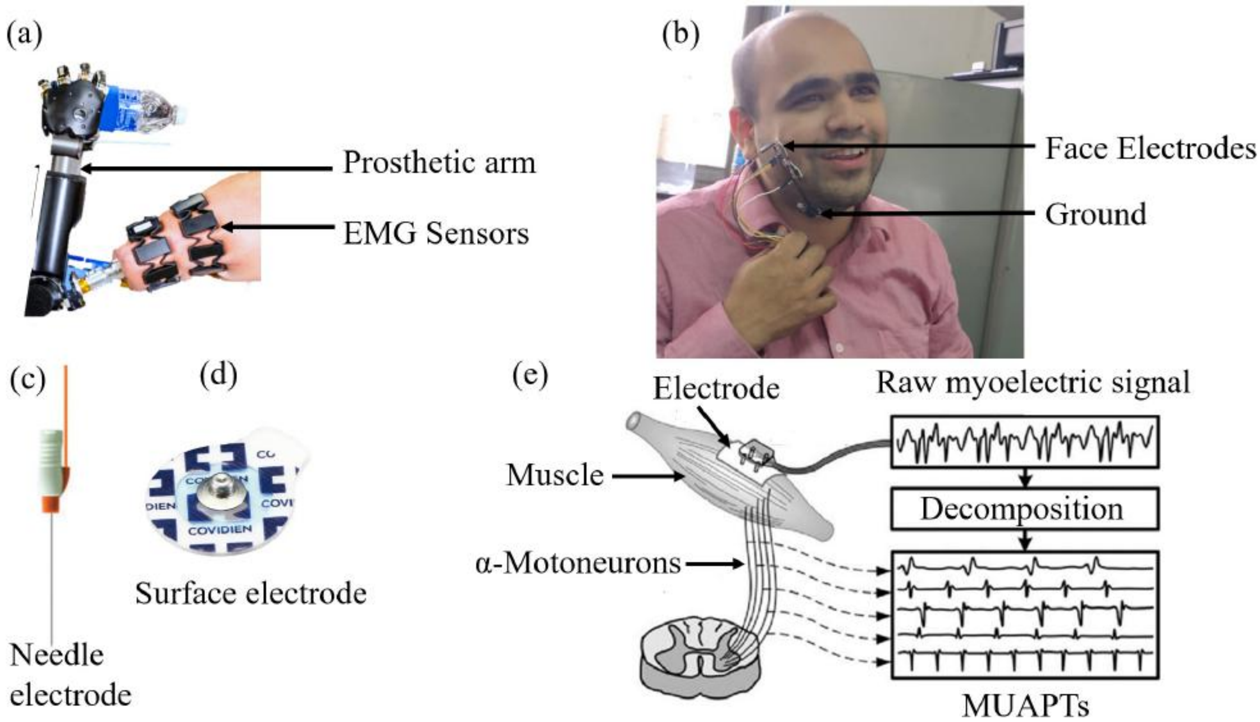

Fig. 1 Different EMG sensor electrode position on human body. (a) EMG sensor placed on biceps to move prosthetic arm. (b) EMG signal placed on the surface of human cheek for speech recognition (c) Needle electrode (d) Surface electrode (e) A schematic representation for the decomposition of the myoelectric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

pear in different patterns and 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.

2 Speech recognition based on EMG signal

Many researchers have used EMG for speech recognition [3] (fig. 1 (b)). Their recognition rate achieved lies between 68 % to 97 % with an average success rate of 85.4 %. Recently, Meltzner *et al.* [4] have developed an innovative method of speech recognition using EMG signals from the face. They used signal acquisition and processing techniques [5] on surface EMG (sEMG) [6]. Traditionally, the microphones are used for speech recognition, but the removal of surrounding noise is the major task, so alternatively the EMG sensors can now be used for speech recognition. The people who can't speak can even convey the message through a computerized voice using this EMG method. They have achieved 92.1 % accuracy. Figure 3 (a) shows different sEMG sensor locations. Sensors 1 and 2 shows submental neck, Sensor 3 and 4 shows ventromedial neck, sensors 5 and 6 shows supralabial face position and infralabial face placement is indicated by 7 and 8. Chan *et al.* [7] have worked on the myoelectric signals (fig. 3 (c)) to augment speech recognition (ASR) with an accuracy of 93 %. Jou *et al.* [8] have worked on articulatory feature classification using sEMG and for this, they achieved an accuracy of 68 %. Lee [9] in his research of EMG-Based Speech Recognition using hidden Markov models with global control variables achieved an accuracy of 87 %.

3 Robotic applications based on EMG signal

EMG signals are used as an input in lot of robotic applications[10,11]. Khan *et al.* [12] 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 very good signal to noise ratio [13]. Fig 2 (a) shows the dc-coupled amplification circuit that was employed by the group 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 pin 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 resistance (R) is 120 Ω. INA121 IC requires 9 volts DC supply connected

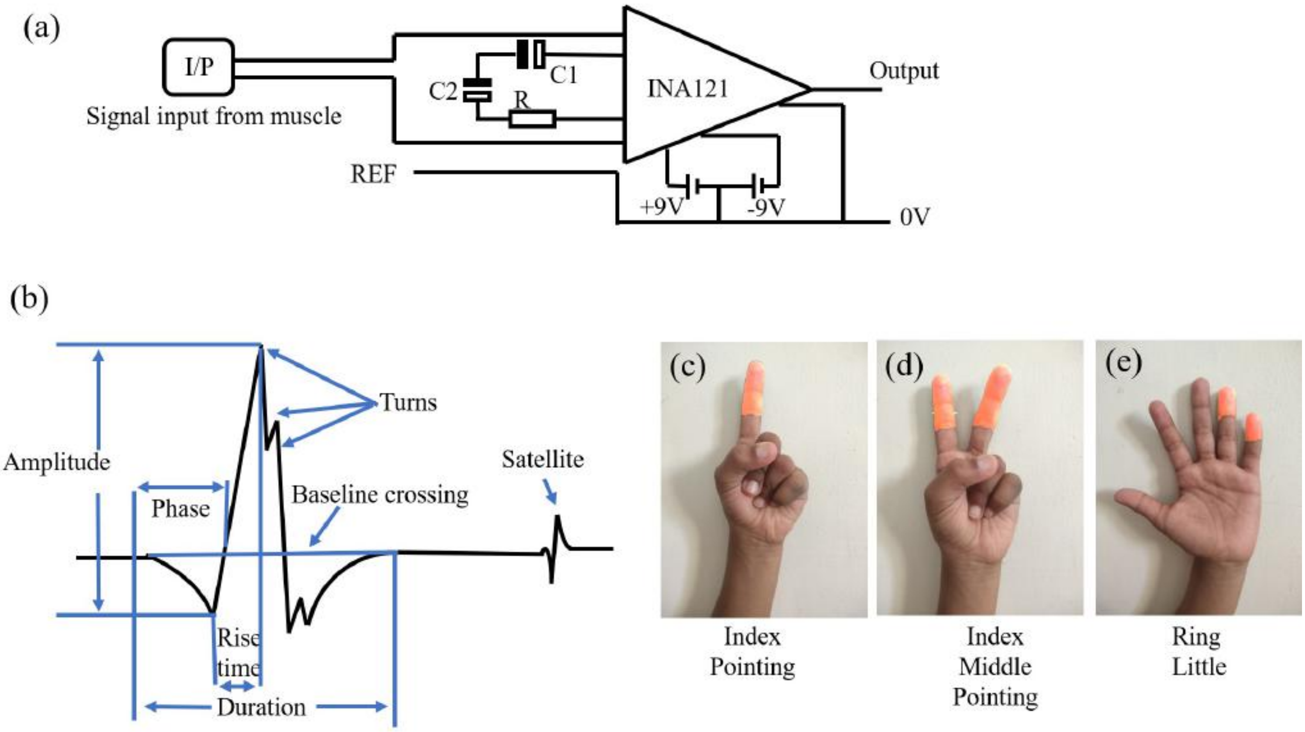

Fig. 2 (a) EMG amplifier circuit with DC coupling. (b) Temporal characteristics of EMG signal. Different positions of fingers while hand is on steering wheel e.g. index finger open (c), index and middle finger open (d), Ring & little fingers open (e).

between pin 7 and 4, The output is collected across pin 6 and reference pin 5. Samarawickrama *et al.* [14] have analyzed the sEMG w.r.t upper limb and flexion angle. They have used INA128 amplifier and UAF42 filter IC. They have classified the signals for the operation of prosthetic limbs. Jamal [15] has talked about signal acquisition using surface EMG [16] and circuit design considerations for robotic prosthesis [17] and explained all the different types of electrodes used in EMG signal analysis and how to place them to get the accurate EMG signal. In this work following electrodes are explained needle electrode, fine wire electrode, surface EMG electrodes [18].

4 Diagnostics applications based on EMG signal

Pauk [19] has talked about different techniques for EMG signal processing. In his work functional evaluation of 20 patients having spastic diplegia was carried out. Spastic diplegia is a form of cerebral palsy (CP) that is a chronic neuromuscular condition of hypertonia and spasticity. The demographic data received was studied carefully and a raw EMG data was made. Witman *et al.* [20] have explained the methods to get EMG signals and analyze it for finger movement. They have used Myoware (fig. 3 (d)) device with an ATmega 329P microcontroller. The finger movements were classified into 5 types. The acquired signals are transmitted using Bluetooth. For classification, they have used K-nearest neighbors (K-nn). They achieved an accuracy of 99.1 % for finger movement. The figure 3 (b) shows electrodes are placed on the channel slots to ensure that they are fixed properly and don't move. The Bluetooth connection is used, for data transmission from EMG hardware and received using a computer. Nardo *et al.* [21] have developed a statistical analysis tool for EMG signal acquired from Tibialis Anterior (TA) during Gait. During acceleration, deceleration, and changes in the direction, the pattern was acquired. They found about 20 % of the total strides were TA active using the EMG signal.

5 EMG signal acquisition and processing

Pancholi *et al.* [22] have developed a low-cost EMG system for the acquisition of Arm Activities Recognition (AAR). They found 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 figure 4 (b - h).

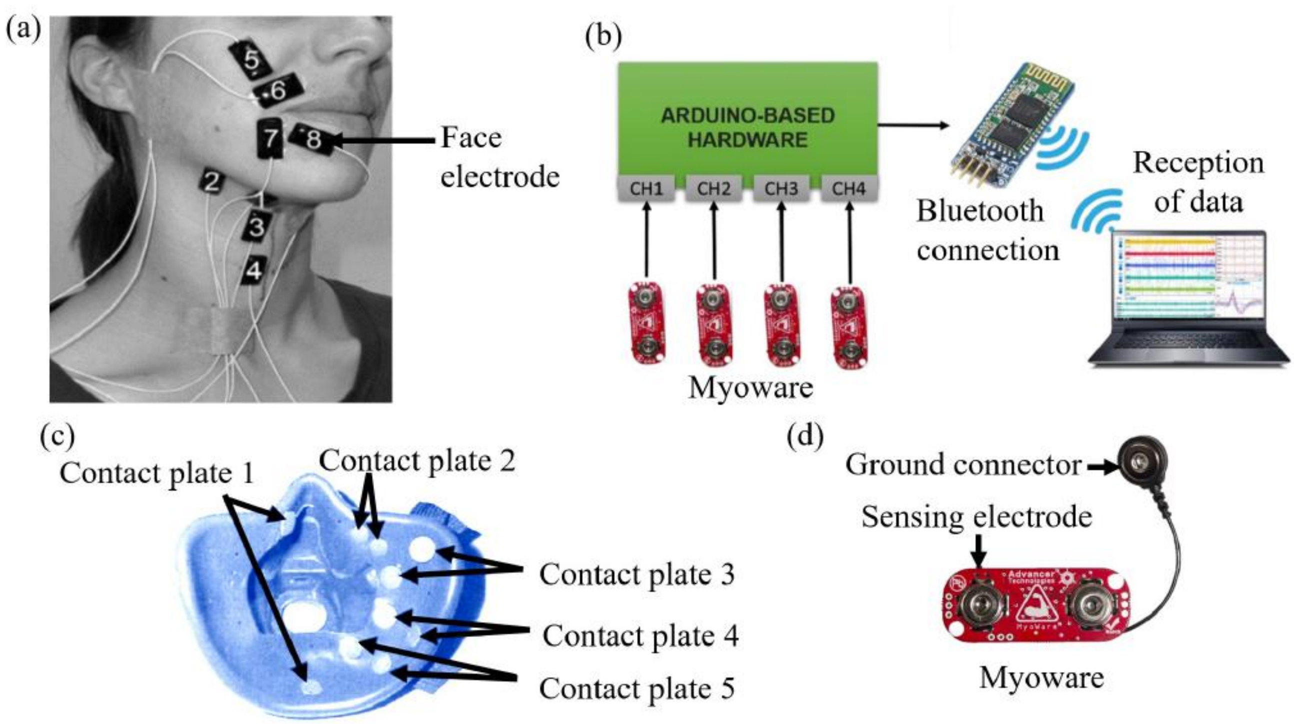

Fig. 3 (a) Different positions on the face, where electrodes should be placed to acquire proper EMG signal. (b) Portable EMG reader. Multiple myoware connected to Arduino and HC05 is used to transfer the data. (c) Face plate with electrodes for speech recognition. (d) Myoware sensor

Reaz *et al.* [23] have presented work on various obstacles (e.g. noise) that interrupt EMG signal acquisition. They also explained how to detect them and classify them into various forms. Shiavi *et al.* [24] 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.* [25] have compared multiple EMG acquisition setups on hand movement with an acquisition efficiency of 54 %. Mambrito *et al.* [26,27] have described a system for acquiring, processing, and also decomposing EMG signal to extract as many Motor Unit Action Potential (MUAPs) (Fig.1 (e)) as possible with the accuracy of 99.8 %. Khusaba *et al.* [28] 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 decides how concentrated the driver is while driving. Fig 2 (c),(d),(e) shows different classes considered in the fingers pressure based experiment [29].

These positions are typical driver's finger positions taken by the hand kept on the steering wheel. Fig 2 (c) shows index finger open. Fig 2 (d) index and middle finger open and (e) shows Ring & little fingers open.

Gijsberts *et al.* [30] have developed the novel movement error rate for the evaluation of machine learning methods. These methods were tested on sEMG-based hand movement signal classification and found the effectiveness of signal capture is around 60 % and the accuracy of signal recognition is about 82 %. Milosevic *et al.* [31] have presented work regarding challenges that are related to design issues such as electrodes and complexity and constraints of the processing. They have tested EMG signal recognition with 3 datasets (viz. NINAPRO, UNIBO, Cerebro). It was found that accuracy was 76.3 % for NINAPRO (All), 89.8 % for NINAPRO (Reduced), 88.9% for UNIBO, and 89.2 % for Cerebro.

6 Analysis and Discussion

For analysis purpose, we have taken multiple literature papers and found out their capture efficiency and recognition accuracy [35]. Recognition accuracy is defined as the ability to correctly classify [36] the action required and action predicted by EMG signal decoding. While EMG capture efficiency is defined by the ability to accurately capture the EMG signals with respect to standard Electromyogram. As per table 1, we found that the recognition accuracy ranges from 68 % to 99.8 %. The majority of the work reported in literature we

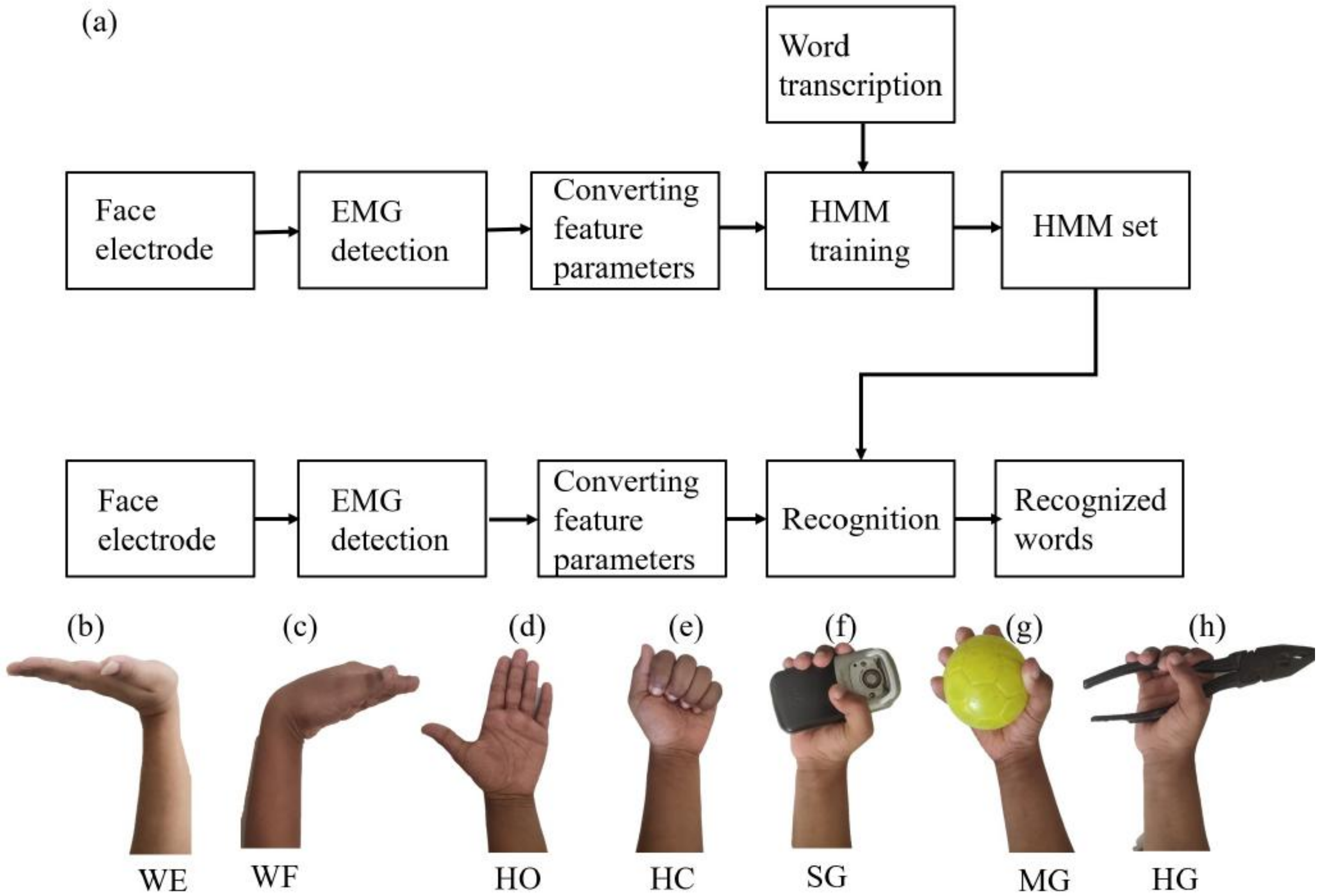

Fig. 4 (a) Block diagram of EMG based Automatic speech recognition (ASR) system. The upper of block diagram shows the offline (training) procedure. The lower part of the block diagram shows an online (recognition) procedure. Various arm positions (b) Wrist Extension (c) Wrist Flexion (d) Hand Open (e) Hand Close (f) Soft Gripping (g) Medium Gripping (h) Hard Gripping

	Recognition Accuracy (%)	**Capture Efficiency (%)**
Meltzner *et al.* [4]	92.1	–
Gijsberts *et al.* [30]	82	60
Atzori *et al.* [32]	–	70
Chan *et al.* [7]	93	–
Betts *et al.* [33]	74	–
Jou *et al.* [8]	68	–
Lee *et al.* [9]	87	–
Pizzolato *et al.* [25]	–	54
Benatti *et al.* [34]	89.2	–
Milosevic *et al.* [31]	89.8	–
Shiavi *et al.*[24]	99	–
Mambrito *et al.* [26]	99.8	–
Pancholi *et al.* [22]	78.85	80
Witman *et al.* [20]	99.1	–
Khushaba *et al.* [28]	93	–

Table 1 Comparison of different EMG systems with respect to the efficiency of EMG capture and accuracy of recognition.

found that recognition accuracy is more than 90 %. Hence there is a slight scope of improvement in recognition accuracy. The captured efficiency of EMG signals is considerably low and lies 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.
2. Needle electrodes gives equivalent accuracy to the surface electrodes, hence user should always go for surface electrode type EMG reader.
3. Surface electrodes are noninvasive and hence must be preferred always.
4. For accurate results, myoware sensors are preferred over low-cost sensors.
5. One can also take the EMG signals while bending the finger to find the sensitivity of the system.
6. Speech recognition is more precise and very convenient using EMG for the deaf and dumb person.
7. To acquire the EMG signal of the limbs, the most suitable place is to take the signal from the back muscle, i.e. behind tibia bone.

7 Conclusion

EMG signals are widely used in robotics to develop prosthetic arms and legs. They are widely used for speech recognition as well. Literature has proven proper EMG signals can be read through non-invasive surface electrodes, hence it is highly recommended to used surface electrodes over traditional needle electrodes. Noise is still a big issue that affects capturing efficiency of EMG signal. But with proper filtering, captured signal can improve up to 40 dB. The Machine learning and deep learning approaches in EMG signal analysis is the next big thing that can take recognition accuracy more than 99 %. For EMG signals in medical analysis applications, athletes and trainers can use EMG as a proper feedback signal and the level of coaching can be taken to a whole different level. EMG is one of the most important and easy to capture the biomedical signal, and a lot of patients with a disability can be profited from its acquisition and recognition.

8 Conflict of interest

Authors has nothing to disclose.

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