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The upper limb of the body is a vital for various kind of activities for human. The complete or partial loss of the upper limb would lead to a significant impact on daily activities of the amputees. EMG carries important information of human physique which helps to decode the various functionalities of human arm. EMG signal based bionics and prosthesis have gained huge research attention over the past decade. Conventional EMG-PR based prosthesis struggles to give accurate performance due to off-line training used and incapability to compensate for electrode position shift and change in arm position. This work proposes online training and incremental learning based system for upper limb prosthetic application. This system consists of ADS1298 as AFE (analog front end) and a 32 bit arm cortex-m4 processor for DSP (digital signal processing). The system has been tested for both intact and amputated subjects. Time derivative moment based features have been implemented and utilized for effective pattern classification. Initially, system have been trained for four classes using the on-line training process later on the number of classes have been incremented on user demand till eleven, and system performance has been evaluated. The system yielded a completion rate of 100% for healthy and amputated subjects when four motions have been considered. Further 94.33% and 92% completion rate have been showcased by the system when the number of classes increased to eleven for healthy and amputees respectively. The motion efficacy test is also evaluated for all the subjects. The highest efficacy rate of 91.23% and 88.64% are observed for intact and amputated subjects respectively.

Keywords Amputees, Classification, EMG, Feature extraction, Incremental learning, Pattern classification, Prosthetic, Real-time, On-line learning.

1 Introduction

The generation of electrical impulses through muscles of the body is termed as "Myoelectric". Myoelectric signals are measurable signals which emerge during muscle activation that is generated due to a small electric current produced by the ion exchange across the muscle membranes. It has wide range of application specially for artificial limb control. The prostheses based on Myoelectric uses the motors along with on the board batteries for the purpose of controlling the robotic devices. They are ultimately useful for the controlled movement of residual limb where input has been derived as electrical signals generated from the muscles. The user intention has been observed through electrodes places from skin to detect the signals of muscles for prosthetic control. The muscles potential has been observed corresponding to various activities such as hand open or close, wrists rotation, grasping etc. The potential would vary on the muscles for various associated activities which are measured for identification of particular activity. The myoelectric prosthesis has advantages over other body-powered devices such as minimization of harness, easier way to identification of pattern, and reasonable hand movements support \[1\]. There have been several Myoelectric technologies available for the upper limb prosthetic control. However, the main challenge is to control robotic arm with neural signal from human for various hand activities control. The electromyography signal (EMG) has considered as one of the best signal to resemble the human physiology.
Electromyography signal is widely used as a control signal for human assistive devices [2], human-robot interface (HRI) [3] and prosthesis applications [4, 5]. The pattern recognition is a technique in which classification algorithm is used for decoding user’s intentions. Several studies have been carried out for EMG-PR (EMG pattern recognition) based system development but they faces the limitations of poor performance and incapability to perform on-line training for multiple classes. The EMG-PR system includes two major parts: (1) extract relevant parameters or features from EMG signal, (2) recognize these features in terms of different classes. The feature extraction methods can be classified in time domain (MAV, WL, ZC, and SSC) [6, 7], frequency domain (mean frequency, peak frequency power) [8], and time-frequency domain (wavelet transform, stockwell transform) based features [9]. In the research [10], time domain features have exhibited improved results than frequency domain features. However, the outcome of the time domain features tends to decrease as the number of homogeneous activities increases. The frequency-domain features are less effective and exhibit poor pattern classification performance in comparison with time-domain features [11]. Phinyomark et. al [12] explored and modified MDF and MNF as modified median frequency (MMDF) and modified mean frequency (MMNF) respectively after removing white Gaussian noise. These modified features had shown better robustness and classification performance of EMG signal.

The features based on wavelet transform is being used in two forms: (i) continuous wavelet transform (CWT) and (ii) discrete wavelet transform (DWT). The DWT proves to be a more effective and consistent method than CWT based features. In the DWT method, the EMG signal is transformed into multiple resolution coefficients and consequently, it takes more processing time [13]. Wang et al. [14] proposed a novel method for precisely producing hand grasp force from sEMG values using wavelet method. Features based on wavelet packet decomposition (WPD) has been exhibited improvisation in classification of homogeneous activities but it shows high computation complexity [15]. In the study [16], time derivative moment based features have been suggested for homogeneous upper limb motion classification. These features leverage both time and frequency with less computation complexity.

The paper flow is as follows: Section 2 includes the related work for EMG based prosthesis control along with novel contribution. The section 3 describes the system architecture along with the acquisition of EMG signals. Section 4 explains the novel technique of features extraction for EMG based pattern recognition. Section 5 covers the performance evaluation of proposed work. Results and discussions are listed in Section 6. Subsequently, the conclusion is drawn from Section 7.

2 Related Work

The usage of EMG for the prosthetic application was started from 1948. The commercial product related to prosthetic control with aid of stepper motor was began in Moscow (Russia) at Central Prosthetic Research Institute during 1957. Subsequently, the design was updated with Magnet DC motor and electromagnetic relays. Afterwards, the development of myoelectric control was seen the remarkable growth for the prosthetic applications. The EMG value is helpful for information decoding in myoelectric control from extracted EMG for the on/off mechanism of motor. The focus is to replace the missing limb part with myoelectric prostheses for the amputees to perform their daily routine tasks. The pattern-recognition algorithms have been successfully found to decode the movement intent and are used extensively in the research work. The various classification techniques are used widely to measure the finger and wrist
movement of the user. The performance at real-time has been observed with amputees in only few of the earlier work. Moreover, such types of solution have very limited acceptance among the people. The accuracy for the classification may be improved with increasing the EMG sensors. The more number of sensors may not be convenient for the user. Hence, there has been conscious efforts are going on for next generation of myoelectronic prosthesis control with multi-model approach with minimum usage of sensors. The prosthetic control can be done using EMG or EEG signal [17]. There are various Brain Computer Interface application were developed using EEG. There various EEG based solutions have been attempted in medical engineering using Intelligent techniques [18]. However, EMG has been used extensively due to easier acquisition.

The classification algorithms such as LDA (linear discriminant analysis), QDA (quadratic discriminant analysis), SVM (support vector machine), k-NN (k nearest neighbor), and ANN (artificial neural networks) have been extensively utilized for EMG-PR based system [19, 20, 21]. In the literature, many EMG-PR based systems have been proposed for upper limb, where the data processing for EMG was carried out through off-line mode with laboratory computer [22]. Portable and wireless EMG signal acquisition system were also reported in the work [8]. Sensor fusion based techniques such as EMG-accelerometer, EMG-NIRs (near infrared), and EMG-ultrasound wave also suggested to improve the pattern recognition rate [22, 23, 24, 25]. The disadvantages of these techniques are high power requirement and system becomes cumbersome. Several standalone system have also been suggested which have utilized SVM, ANN, and LDA [21, 26]. The major drawback of these systems lie in the fact that they are implemented for a single training process.

In case of any activity (or class) is being included then it is required to implement again from the scratch which can lead to time and process overheads. This issue has been coped up in research [27], where an incremental learning based system have been proposed for class extension [28, 29, 30]. Incremental learning is an emerging technique in machine learning based system development. In this technique, the current knowledge of the system fully preserves and modifies the original information using the knowledge learned from the new samples. The basic flow diagram of incremental learning based EMG-PR based system has been shown in the Fig. 1. The big advantage of incremental learning is that when new samples are added into the system, there is no requirement to retrain the whole system again. This helps to reduce memory consumption and training time. Incremental learning is also very suitable for learning outside the development process, allowing devices to respond to specific user habits and conditions. Efforts on simultaneous control of multi-DoF (degree of freedom) EMG-based prostheses have been made, but much more remains to be done [31]. Recently, the HD-EMG signal-based systems have been performing exceptionally well [32]. A hand gesture recognition system based on EMG was developed, and it performed admirably, with more than 92 percent classification accuracy [33]. However, only healthy people were taken into account. The system also has a large number of EMG channels (64), which increases the system’s power consumption. Another study with abled-body subjects has been reported [34]. Hand gestures were predicted using CNN and transfer learning techniques in this study. This system also employed a high-definition EMG signal, which has the disadvantage of being computationally
demanding. The incremental learning-based system with wavelet neural network (WNN) utilisation has been proposed [9], which is capable of improving classification performance through continuous learning. The system can effectively classify up to six hand gestures for amputated subjects. The WNN is more complex than time-domain based approach and discriminant analysis based classification techniques.

Figure 3: Adjustable band of Ag-AgCl patches on upper limb: (a) Anterior view (b) Posterior view with proposed system

2.1 Novel contribution

The proposed work is able to overcome all the drawbacks and the main contributions of the proposed work are as follows:

1. A new feature extraction approach has been implemented and tested in real-time for effective EMG-PR.
2. An incremental learning based EMG-PR system has been developed for upper limb amputees.
3. The system can classify up 11 upper limb motions with reasonable classification accuracy on amputated subjects.
4. The pattern completion performance is evaluated using motion completion test and motion efficacy test.

3 Methodology

The proposed methodology has been also validated on amputees subjects. The EMG acquisition module has been designed with surface electrodes, ADC, differential amplifier, display system and anti-aliasing filter [8]. The acquisition module also uses ARM cortex M4 and TI based ADS1298. The easier user interface has been created with GUI for analysis of each channel data.

3.1 System Architecture

This system has an ADS1298 as an AFE (analog front end) with an 8-channel differential feed, an advanced band with adjustable strap, and a power control circuit. This band has metallic $Ag - AgCl$ patches for the acquisition of EMG signals using a non-invasive process. Protection circuits have been integrated before the input of each channel with a resistance of $200\Omega$ to maintain high input impedance. For digital signal processing, a DSP processor of 32 bit with arm cortex-M4 core was used. With a 3.7V lithium-ion battery, the power supply to the circuit is provided. The DSP processor runs at a 150 MHz device clock, and the algorithm is implemented using the built-in FPU (floating point unit).

The data acquisition frequency has been set at $1000 SPS$ (samples per second). In order to eliminate DC and power line noises, a $3^{rd}$ order IIR BPF (band pass filter) filter have been realized from 10 Hz to $500 Hz$ frequency range and it
Figure 4: (a) Rest (b) Hand close (c) Hand open (d) Wrist extension (e) Wrist flexion (f) Cutter grasp (g) plier grasp (h) Screw grasp (i) Quapod grasp (j) Large diameter grasp (k) Normal parallel extension grasp (l) Forced parallel extension grasp

is cascaded with 2\textsuperscript{nd} order 50Hz notch filter. The coefficients of these filters have been extracted using the MATLAB 2015a software. The incremental learning based LDA classifier has been implemented, which takes input from the user for class extension. The flow chart of this algorithm has been shown in the Fig. 2. Data from 8-channel differential inputs are collected in the circular buffer after digitization of the raw EMG signal via AFE. This data is employed for feature extraction afterwards the propose algorithm uses these features for the training process for specific activity. The proposed system is show in the Fig. 3.

3.2 EMG Signal Acquisition and Experimental Setup

1. Total 8 electrodes have been employed around the forearm of the residual part of the limb for EMG signal acquisition as depicted in the Fig. 3. Similar electrode positions have been considered for healthy subjects.

2. Total 8 subjects including 5 intact and healthy male subjects (age: 22±4.2) and 3 amputees have been recruited for this study. The information of the amputated subjects is given in the Table 1.

| ID   | Age | Height (cm) | Weight (kg) | Reason of Amputation | Years since Amputation |
|------|-----|-------------|-------------|----------------------|------------------------|
| Amp-A| 27  | 170         | 65          | Trauma               | 2.5                    |
| Amp-B| 60  | 172         | 80          | Trauma               | 10                     |
| Amp-C| 40  | 168         | 72          | Trauma               | 8                      |

3. A computer screen has been incorporated at the from of each subject for the visual instruction.

4. After primary training facilitation, total 11 arm exercises have been performed by each subject as show in Fig. 4.
5. After each run, 2 minutes break has been given to avoid muscle fatigue.

4 ATDM Feature Extraction Scheme for EMG-PR

The novel scheme for pattern recognition has been proposed using time domain features. The proposed scheme is robust and effective for real-time implementation. The proposed scheme is defined as “ATDM (Advanced Time Derivative Moment)” provides higher classification accuracy for various activities in myoelectric control. The proposed novel ATDM technique uses time domain along with frequency components information from EMG signal. The technique was also tested on various scientific data test along with amputees subjects. The performance was observed excellent in terms of scatter plots, timing analysis and DB index criteria in comparison to other previous work.

In the EMG-PR based system, features are typically extracted manually and require in-depth knowledge of the biological process that underlies the generation of the EMG signal during muscle movement. The sEMG is obtained via the convolution of the motor unit action potential of each motor neuron spike-train. In the EMG time series, the two important variables differ predominantly: (i) the number of peaks that occur during muscle contraction, which corresponds to the frequency information of the signal, and (ii) the time series amplitude or energy level, which provides information about the intensity of a specific operation. We therefore devise an advantageous and efficient technique called ATDM (Advanced Time Derivative Moment) features for reliable and robust knowledge extraction.

In this work the following parameters have been taken for proposed feature extraction approach.

The \(n^{th}\) functional derivative of \(x[j]\) can be calculated by the multiplication of the frequency spectrum of \(x[j]\) and \(k\) raised to \(n^{th}\) as shown in the equation 1 as stated in the Fourier transform time differential property.

\[
F[\Delta^n x[j]] = k^n X[k]
\]  

where \(\Delta^n\) represents the \(n^{th}\) derivative and \(X[k]\) is the power spectrum of \(x[j]\), and \(k\) shows the frequency index varies from \(k=0\) to \(N-1\).

To extract features for decoding human intent using EMG signal the power spectral moments are utilized. The \(n^{th}\) order moment \((m)\) of \(x[j]\) can be calculated through its power spectral density \(X[k]\) and is represented by the equation 2.

\[
m_n = \sqrt{\sum_{k=0}^{L-1} K^n X[k]}
\]

where \(L\) represents frame size or window length.

As stated in the parseval theorem [35], the SOS (sum of square) of the segmented signal can be defined by its power \(P\) as below.

\[
\sum_{j=0}^{L-1} |x[j]|^2 = \frac{1}{L} \sum_{k=0}^{L-1} |X[k]|^2 = \sum_{k=0}^{L-1} P[k]
\]

Using equations 1, 2, and 3, the \(0^{th}\) order moment \((m_0)\), and the \(2^{nd}\) order time derivative moment can be determined as shown in equations 4 and 5 respectively.

\[
m_0 = \sqrt{\sum_{j=0}^{L-1} (x[j])^2}
\]

\[
m_2 = \sqrt{\sum_{j=0}^{L-1} (\Delta x[j])^2}
\]
Similarly, fourth order moment has been denoted in equation (6).

\[ m_4 = \sqrt{\sum_{k=0}^{L-1} k^4 P[k]} = \sqrt{\sum_{j=0}^{L-1} (\Delta^2 x[j])^2} \]  

(6)

The number of peaks (NPs) and Number of zero-crossings (ZCs) can be formulated in terms of their spectral movements in a stochastic process. The ratio of fourth order moment to second order moment as NPs, and the ratio of second order to zero order moment as ZCs \[ \text{[36], [16]} \]. These are defined in equations (7) and (8).

\[ NPs = \sqrt{\frac{m_4}{m_2}} \]  

(7)

\[ ZCs = \sqrt{\frac{m_2}{m_0}} \]  

(8)

Further the square version of NPs and ZCs have been utilized to reduce computational complexity as shown in equations (9) and (10) respectively.

\[ NPs = \frac{m_4}{m_2} = \sigma \]  

(9)

\[ ZCs = \frac{m_2}{m_0} = \theta \]  

(10)

The first feature of the PAP (peak average power) is the ratio of the segmented signal power to the square version of NPs (\( \sigma \)). The \( \sigma \) reflects the content of the frequency in the EMG signal. The \( \sigma \) represents the frequency contents in the EMG signal. Therefore, this feature utilizes both time and frequency information (equation (11)).

\[ PAP = \frac{m_0}{\sigma} \]  

(11)

Similarly, the ratio of segmented EMG signal power and square version of ZCs (\( \theta \)) has been considered in the ZCAP (Zero crossing average power) function. This function is similar to PAP and uses details about both time and frequency. This role is efficient when more base line numbers are crossed by the bipolar EMG signal.

\[ ZCAP = \frac{m_0}{\theta} \]  

(12)

Third feature is considered to be a modified variant of the waveform length feature (MWL), denoted in equation (13). In this feature the waveform length feature utilizes after first derivative of the signal.

\[ MWL = \sum_{0}^{L-1} \dot{s}_i - \dot{s}_{i-1} \]  

(13)

Here \( \dot{s} \) is the first derivative of the signal.

Subsequently, the difference between zero order moment and second order moment has been taken to drive fourth feature as denoted in the equation (14). This feature extracts the information of irregularity present in the EMG signal.

\[ DBM = m_0 - m_2 \]  

(14)
4.1 LDA based Incremental Learning

Incremental learning is a method through which the model is trained incrementally using new data. The key advantage of incremental learning is that the generated model dynamically adapts to new patterns in the current model parameters. The linear discriminant analysis based classifier has the inherent advantage of low operational memory overheads. This is due to its principle of operation where a single pooled co-variance matrix gets utilized irrespective of the number of presence of the classes. Let us assume that PDF (probability density function) for multivariate Gaussian distribution, \( x \sim D(\mu, \xi) \) is:

\[
f_k(x)\pi_k = \frac{1}{\sqrt{(2\pi)^d |\xi|}} \exp(-\frac{(x - \mu)^T \xi^{-1} (x - \mu)}{2})\pi_k
\]

(15)

where \( x(\text{input}) \in \mathbb{R}^d, \mu(\text{mean}) \in \mathbb{R}^d, \xi \in \mathbb{R}^{d \times d} \) is the covariance matrix, and \(|.|\) is the determinant of matrix. Here \( \pi \approx 3.14 \). Taking natural log the equation becomes as:

\[
ln(f_k(x)\pi_k) = -\frac{d}{2}ln(2\pi) - \frac{1}{2}ln(|\xi|) - \frac{1}{2}(x - \mu_k)^T \xi_k^{-1} (x - \mu_k) + ln(\pi_k)
\]

(16)

\[
\alpha_k(x) = -\frac{1}{2}ln(|\xi_k|) - \frac{1}{2}(x - \mu_k)^T \xi_k^{-1} (x - \mu_k) + ln(\pi_k)
\]

(17)

In the LDA the co-variance matrix is same for all the classes, let us assume it as \( \xi \).

\[
\xi_1 = \ldots = \xi_{|C|} = \xi
\]

(18)

Therefore, above equation will become as

\[
\alpha_k(x) = -\frac{1}{2}ln(|\xi|) - \frac{1}{2}(x - \mu_k)^T \xi^{-1} (x - \mu_k) + ln(\pi_k) = -\frac{1}{2}ln(|\xi|) - \frac{1}{2}x^T \xi^{-1} x - \frac{1}{2}\mu_k^T \xi^{-1} \mu_k + \mu_k^T \xi^{-1} x + ln(\pi_k)
\]

(19)

The constant terms \(-\frac{1}{2}ln(|\xi|)\) and \(-\frac{1}{2}x^T \xi^{-1} x\) can be dropped for the simplification (Note: These two terms are same for all the classes). The final equation will become as:

\[
\alpha_k(x) = \mu_k^T \xi^{-1} x - \frac{1}{2}\mu_k^T \xi^{-1} \mu_k + ln(\pi_k)
\]

(20)

The class of the instance \( x \) is estimated as:

\[
\hat{C} = \arg\max_k \alpha_k(x)
\]

(21)

Let’s assume new class (T) is going to get updated in the existing trained model. The new covariance matrix and mean of that particular class are need to be computed and the existing pooled covariance matrix is being updated as presented below in equation (22).

\[
\xi_{new} = \xi + \xi_T
\]

(22)

The pooled co-variance matrix gets updated by summation of co-variance matrices of individual classes. This overcomes the limitations of conventional methods where individual parameters needs to be stored that can consume huge memory space. This can also aid in on-line training as the system is equipped with the capability of incremental learning where new classes automatically gets added to the pooled co-variance matrix after each iteration. Conventional system face limitation that automatic update is complex that increases the process and computation complexity. The new discriminant function after updating the new class, is denoted in equation (23).

\[
\alpha_k(x) = \mu_k^T \xi^{-1} x - \frac{1}{2}\mu_k^T \xi_T^{-1} \mu_k + ln(\pi_k)
\]

(23)
Figure 5: Real-time incremental learning performance: (a) Healthy subjects, (b) Amputee-A, (c) Amputee-B, (d) Amputee-C

Figure 6: Confusion metrics for amputee-A: (a) for 8 classes and (b) for 11 classes
These four main sub-processes such as signal acquisition, segmentation, feature extraction, and classification (testing) must be performed with a latency of 200-300 ms to satisfy the real-time device constraints. In this work, EMG data was segmented into a series of windows of 200 ms with a window shift of 75 ms. This helps to reduce the non-stationary factor of the signal and makes the signal quasi-stationary.

Table 2: Comparison of the proposed work with recent literature work

| Lit. work | Parameters | Duan et al. (2017) | Pancholi et al. (2019) | Turlapty et al. (2019) | Yu et al. (2019) | Tam et al. (2021) | Moin et al. (2021) | Proposed |
|-----------|------------|-------------------|------------------------|------------------------|------------------|-------------------|-------------------|----------|
| Subject   | No. of classes | Healthy | Healthy/Amp. | Healthy | Healthy | Healthy | Healthy | Healthy/Amp. | Healthy/Amp. |
| Classifier | WNN | LDA | PNN/k-NN | LDA | CNN | LDA | Neuro-inspiredhyperdimensional computing algorithm | LDA |
| Feature Techniques | RMS | RMS, SSC, ZC, WL | Modified spectral moment | MPT | Deep and Transfer learning | Hypervector | ATDM |
| Classification accuracy | 92.17 | 94.14 | 93.9 | 86.61 | 93.43 | 97.12 / 92.87 | 94.14 / 92 |
| Real-time Embedded Incremental | No | Yes | No | No | Yes | Yes | Yes | Yes | Yes |

5 Performance evaluation

In order to evaluate the performance the following metrics are considered:

- **Motion completion (MC):** It is an alternating parameter to measure the performance of proposed technique in real-time scenario. When the proposed algorithm predicts the correct target (motion), the processed feature vector is assigned as a success. The effectiveness of the classifier is calculated as the ratio of right to wrong estimates over the total number of windows (N) and multiplied by 100. A classification score of 100% is considered if subject achieves all motions, whereas score 0% is denoted when no target is achieved as represented in the equation (25).

- **Motion efficacy:** The efficacy of the motion is calculated by combining the classifier prediction and speed of proportional control as shown in the equation (27). Therefore, this metric uses both the classification success rate and the volitional speed to move the prosthetic arm. A score of 100% would suggest the subject controlled the prosthetic arm correctly and smoothly (proper speed). Similarly, a score of 0% exhibits the subject had poor control over the prosthetic limb and failed to achieve the target motion.

\[
\text{prop}_n^{\text{pro}} = \text{prop}_n \ast \text{est}_n^{\text{pro}}
\]  \hspace{1cm} (24)

\[
\text{MC} = \left( \frac{\sum_{n=1}^{N} \text{est}_n^{\text{pro}}}{N} \right) \ast 100
\]  \hspace{1cm} (25)

Here \(\text{prop}_n\) represents the volitional speed used to control the prosthetic limb.

\[
\text{est}_n^{\text{pro}} = \begin{cases} 
1 & \text{if subject achieves the motion} \\
0 & \text{if no motion or wrong motion}
\end{cases}
\]  \hspace{1cm} (26)

\[
\text{eff}_{\text{motion}} = \left[ \sum_{1}^{n} \frac{\text{prop}_n^{\text{pro}}}{\text{prop}_n} \right]
\]  \hspace{1cm} (27)
6 Result and Discussion

6.1 Motion completion performance

In order to evaluate the accuracy of the proposed system, the subject is asked to repeat each motion 30 times. In this work, 4 classes have been taken into initial consideration which later on gets incremented till 11 classes and testing has been performed. The accuracy of the classifier has been evaluated initially for four classes and letter on accuracy for individual class increments have been analysed and depicted in the Fig. 5 (a) for intact subjects. The classification rate patterns are summarized for each amputees (b), (c), and (d). The initial motion completion rate is found to be 100% which stays as such when number of classes are increased to 5 for healthy subjects. Further when number of classes is increased to 11, completion rate observe of 94.33% and ≈ 92% for healthy and amputated subjects respectively. The confusion matrices for amputated subject (B) is also presented in the Fig. 6 when 8 motions and 11 motions are considered. These confusion matrices shows that system has performed well with high TP (True positive) and TN (True negative) values. The proposed system, due to its capability of online training and incremental learning overcomes the limitations of existing systems.

6.2 Motion efficacy

The motion efficacy of all subjects including healthy and amputees is shown in the Fig. 7. This represents that the higher and smooth classification performance within the time frame and speed. The healthy subject shows above 91.23% efficacy rate. The highest motion efficacy rate 88.64% has been obtained when amputated subjects are considered.

The comparison with state of art systems is summarized in the Table 2. Existing system have been tested only for intact subjects 26. In the research 41, the performance of the proposed technique was evaluated using online testing but system was not realized on embedded platform. In the studies 39, 40, 9, only off-line analysis was performed and no real-time adaptation for the system. Moreover, the complex classification algorithms such as wavelet neural network and convolutional neural network were adopted. However, for real time implementation robustness of system needs to be ensured. In this work, versatile data sets including amputees have been used for system validation with real time incremental learning on embedded platform. Furthermore, the ANOVA (Bonferroni with 95% confidence level) test has been utilized to validated the real-time feasibility. The online evaluation gives more than 90% motion completion rate (p > 0.01) and more than 90% motion efficacy (p > 0.048). It is observed that there is a significant improvement in motion completion and motion efficacy performance with respect to TD features and time-frequency (wavelet) at p < 0.031.

The computational complexity of different state of art techniques is given in the Table 3. It can easily be understood that LDA shows low computational complexity with a minimum number of necessary operators (adder and multiplier).

| Classifier | Add(+) | Mul(x) | Sqr (\(\cdot\)²) | Sqrt (\(\cdot\)²) |
|------------|--------|--------|----------------|----------------|
| LDA | W     | W     | 0 0 |       |
| QDA | W+W   | W+W   | W 0 |       |
| SVM(L) | (W+1)Q-1 | (W+2)Q | 0 0 |       |
| SVM(Q) | (W+2)Q-1 | (W+2)Q | Q 0 |       |
| k-NN | 2(S(W+1)-6) | 0 | SW | S     |

Note: W, Q, and S are dimension of the feature vector, the number of support vectors (SVs), and the required training samples, respectively. Add: Adder, Mul: Multiplexer, and Sqr (\(\cdot\)²): Square, and Sqrt (\(\cdot\)²): Square root

The power breakdown of training process has been presented in the Fig. 8. The amount of energy consumed is proportional to the number of channels used and the sampling frequency, which in our case was 7.1 mW for 8 channels at 1000 SPS. The feature extraction process consumes more power which is 36.2 % of the total power (134mW) consumption of the proposed system.

Following that, the time spent on each sub-task during the training process is calculated, as shown in Table 4. Feature extraction consumes the most time, 90.88 ms. The LDA parameter calculation takes 8.23 ms for each task which includes pool co-variance matrix calculation. When the system has been trained and the parameters for each task have been calculated, the testing phase can begin. The testing phase takes 4.1ms for each upper limb activities and 49.2ms all activities. The total features require maximum 9600 bytes, which can easily be stored on 1 MB of flash memory.
Figure 7: motion efficacy of test result

Table 4: Time consumption of each sub-task in our proposed embedded system

| S.No. | Task                                      | Time   |
|-------|-------------------------------------------|--------|
| 1.    | Data storing into circular buffer         | 75.7 ms|
| 2.    | Pre-processing                            | 10.65 ms|
| 3.    | Feature extraction                        | 90.88 ms|
| 4.    | Training parameter calculation for each task | 8.23 ms|
| 5.    | Testing parameter calculation for each task | 4.1 ms |

Figure 8: Power breakdown diagram of the system for each sub-processes including emg signal acquisition, noise reduction, feature extraction, and classification
7 Conclusion

The paper presents an incremental learning based EMG-PR system that has been validated for intact and amputated subjects. The system shows enhanced performance over existing systems overcoming their limitations of off-line training and increased processed overheads with class extension. Time derivative moment based features have been used due to its advantage of utilizing time and frequency domain information without any transformation. Moreover, LDA classifier ensures low computation complexity involved.

The future work may focuses on continuous classification for various activities for EMG-PR-based system. There is also some scope of improvement for multiple DoF motions for EMG based prosthetic control. There are still some challenges for long term durability of the proposed system such as a change in muscle signal over a period of time, variability in EMG signal acquisition environment, performance variation due to muscle fatigue, and shifting in the positioning of electrodes.

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