Comparative Study on EMG Signal Analysis and Classification for Leg Prosthetic and Rehabilitation

Ghada kareem , Mohamed Aouf, Mohammed A.-M. Salem

Higher Technological Institute,10th of Ramadan city, ghadakareem5@gmail.com ,maoufmedical@yahoo.com,

Faculty of Media Engineering & Technology, German University in Cairo, ,

mohammed.salem@guc.edu.egthird.author@gmail.com

Abstract– The In the recent years, some studies have focused on powered lower-limb prostheses to enable normal walking gait. However, most proposed prostheses use manual switch to change the locomotion mode, for example from walking to sitting or vice-versa. Intelligent prostheses use micro-processing control for automatic switching by utilizing the advances of signal processing and pattern recognition techniques, where the user's intent could be recognized by analyzing the EMG signals sensed from the lower limb. After the recognition phase, the prosthesis controller controls different prosthesis components, to mimic the natural leg. Introduced in this paper is a comparative study and survey on the recent work on EMG signal analysis is for the purpose of classification and recognition. The paper presents details on the recent work done on each stage of EMG analysis, starting by preprocessing, de-noising, and segmentation through feature extraction till classification. It also presents recent work done using deep learning. The results achieved by the different research groups are summarized at the end of the paper

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Keywords-- Pattern Recognition, User Intent, Control, Active Prostheses, EMG, Deep Learning.

I. Introduction

that replace a part of the arm or the whole arm [4, 5, and 6]. Less work has been done for lower-limb prostheses. Lower-limb prostheses, replace a part of the leg or even the whole leg. These lower-limb prostheses must be reliable and stable to prevent falling while performing different activities. The most important activity that legs do is walking. Walking is not an important There are thousand million people in the world live with disabilities (one in each seven people), of whom two hundred million experience considerable difficulties in functioning [1]. Devices that mimic a missing or malfunctioning part of the body are needed to overcome some types of disabilities. For example, hearing aids that people with hearing-impairment wear behind their ears, amplify the sound coming from the surrounding environment. Another type of devices that people with different type of disability use is the prostheses [2, 3]. Prosthesis is useful for a person with a missing part of his body. Researchers have studied thoroughly upper-limb prostheses activity itself but moving from a place to another to do another desired activity is the vital one.

The movement of human leg differs during different tasks. Its movement during walking is different than when moving during stairs ascending or stepping over an obstacle. Therefore, the artificial leg should perform differently in these tasks. In recent artificial legs, changing mode through different tasks is done manually by the user, either by a switch button or by exaggerating effort done by specific muscles and joints.

The human gait cycle is to be studied to accurately identify different walking modes. For example: the human walk process is cyclic. There are two phases in the cycle, Swing phase (40%), and stance phase (60%). When the foot is totally or partially on the ground that is the stance phase, while the swing phase is when the foot on the air for limb advancement [7, 8, and 9]. To study different human gaits, kinematics (the body movement) and kinetics is forces that affect the body while walking are studied. Kinematics could be recorded through many methodologies:

(1) With the development of photography, Chronophotograph was the basic method. Using a set of still pictures captured after each other, the human gait was analyzed.

(2) Using video recordings from one camera or more are using for measuring velocities and joint angles, that allowed three-dimensional analysis of the walk cycle.

(3) Passive marker systems use infrared radiations and reflective balls set on the human body, allowing more accurate measurements of angle & delay time between anatomical remarks original and reflect signals.

(4) Active marker systems work also with infrared radiations that trigger markers to send signals about their location. To calculate movement kinetics, ground force reaction is measured by load transducers when load transducers are put on the floor.

(5) Electromyography (EMG) sensors are using for measuring the electrical activity of the muscles when being activated.

(6) Another way to measure activity of muscles is the implantable Peripheral Nervous System (PNS) approach, which uses percutaneous electrodes planted in the nerves or using of implantable capsules to extract the signals of EMG.

(7) Finally, implantable Central Nervous System (CNS) approach utilizes arrays of electrode which implanted in brain cortex for extracting commands of motor.

The least invasive approaches are usually better for medical devices. EMG signals approach has the advantage of less invasiveness. Fig. 1 by Neptune et al, shows different muscle activities during a complete gait cycle. The abbreviations of the different muscle groups stand for:

TA:Tibialis Anterior,
IL: Iliacus, psoas,
BFsh: Biceps Femoris short head,
GMAX: Gluteus r Maximus Adductor Magnus,
GAS: Gastrocnemius,
RF: Rectus Femoris,
HAM: Hamstrings, SOL (soleus), and TA (tibialis anterior).
VAS: 3-CcomponentVastus and
SOL: Soleus.

Passive prostheses do not generate power by themselves. They only react to the contact with the ground or the contact with the amputee's body himself. Active prostheses are those that generate power and lessen the energy exerted by amputee wearing them. Powered prostheses include motors to provide power needed to pro-act rather than just react [11, 12, 13, and 14]. Powered prostheses were only commercially available since 2010 [15].

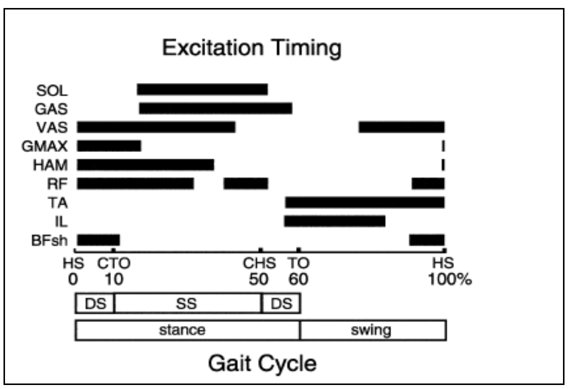

Fig. 1 Muscle excitation timing during a complete gait cycle [10].

II. Gait Analysis and Positive Control

A. The EMG signal processing framework

We are not robots, any human movement cannot be precisely reproduced in the same shape, and this includes gait patterns. Additionally, because raw surface. Spikes of Electromyography (EMG) were of shape randomly, it is not expected that EMG data for several walk cycles of the exact person will be identical. The range of raw surface EMG could be (+or -) 500 µvolts while the range of frequency (6to500) Hertz [40].

First step for EMG processing is converting all amplitude which is negative amplitudes to positive amplitudes, rectification. The Root Mean Square (RMS) are used to smooth the EMG signal, there is no need to use any filter. As mentioned before, your gait patterns are not the same when same movement is done twice. Gait patterns differ when you are moving using different shoe or walking on a different terrain. It even differs when you are tired than when you are full of energy or about to sleep. To overcome this, the EMG signal is normalized to a value which is reference such as the Maximum Voluntary Contraction (MVC) [41, 42]. Participants are asked to make the maximum effort using each muscle separately to check the MVC value of this muscle. The concept of MVC is used in the most of studies which associated with trained and healthy subjects [16]

B. Controlling Lower Limb Prostheses

Echo Control scheme was proposed to control movement of joints in prostheses. This approach as shown in Fig. 2 depended on sensors put on the healthy leg.

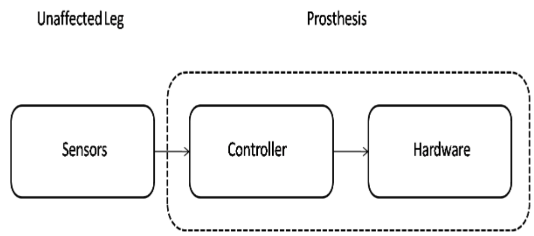

Fig. 2 Echo Control Scheme.

The actions performed by this healthy leg are echoed to be performed on the prosthesis worn on the other side. Echo Control approach has some disadvantages. Firstly, the amputee has to put some equipment on his healthy leg which might not be desired. Secondly, the information that is to be echoed is delayed, nearly half a step before being applied on the prosthesis worn. Thirdly, the amputee will face a problem if he desires to make an odd number of steps. Lastly, this scheme cannot be applied on bi-lateral amputees.

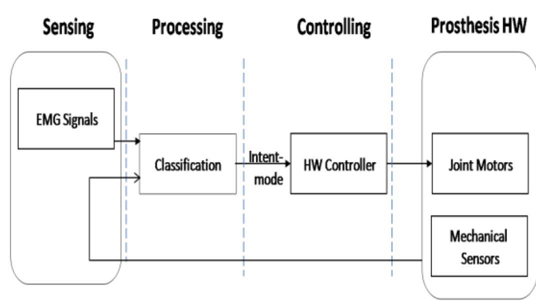

Fig. 3 Gait Intent Recognition System.

Another approach to control powered prostheses is shown in Fig. 3; it is called Gait Intent Recognition.

Sensors are put on the prosthesis and on the residual muscles of the leg with amputation. Output of these sensors is then utilized to recognize the purpose of the user. The result of intent guessing was as then used to control the prosthesis. The advantages of this approach over the echo control system are many. No wiring is needed to be put on the healthy leg. No delay resulting from waiting for the step of the healthy leg to be performed. No constraints on the number of steps. Finally, bi-lateral amputees can benefit from this approach.

In [39] the authors presented a survey on the development of bioelectronic prostheses and orthoses to demine the user's intent of the movements of limbs.
Huseyin et al. [17] suggested a real-time gait intent recognition system for both standing and walking modes and tested it to control both of prosthesis ankle and Knee powered. The system recognized patterns of the output coming from sensors put on the prosthesis (mechanical sensors only). A non-amputee subject did the experiments on a treadmill using an able-bodied adapter designed in [13].
Test the performance of the suggested work by asking the subject to walk in three walking speeds fast, slow and normal. During Standing, he was demanded to randomly shift weight of him among limbs, and then turn in place and still stand. Principal Component Analysis (PCA) reduced the dimension with 100 sample of the frames long gave good results by utilizing a GMM classifier. The results of this study were encouraging that an amputee was recruited to test it in 2010 [18]. In this study, sitting mode was added to the experiments. The results were also good and satisfying. A further study [19], studied a system for walking on a slope with two different slope angles (5º and 10º) was experimented. Suggested controller gave better results than walking upslope with passive prosthesis.
Au et al., [20], introduced a comparison for predicting user's intent through Neural Network and muscle model EMG-controller approaches. For simplifications, only movements of sagittal plane of the ankle joint are addressed for a transtibial (below knee) amputee, dorsiflexion, and ankle plantar flexion. EMG data from three muscles (Gastrocnemius, Soleus and Tibialis Anterior muscles) was measured. The amputee participant included in this study watched ankle movements on a screen and tried to mimic them. EMG data measured from his muscles are using as offline data training. The next step to this work is to evolve the algorithms of real-time learning to control EMG.
In [21], mechanical sensors on prosthesis, previously designed in [22], control stair descent gaits and the mimic of level-ground. But the control of prosthesis transition between these two gaits was using EMG data as input. The two muscles (Gastrocnemius and Tibialis Anterior) were studied to control these transitions. EMG is using for the limb residual such as control commands that allow the transition control mode is quick.
Chen et al. [35], utilized different leaner regression to demonstrate the arm movement and getting a force from EMG signals procured from five lower arm muscles. Objects were teaching to complete three sorts of calibration errands to prepare the demonstration and one deliberately shifting getting a handle on drive errand to test the demonstrate execution. The getting a handle on constrain applied by each subject was constrained to be lower than 50% greatest voluntary contraction (MVC) getting a handle on drive. Mean absolute difference (MAD) between anticipated and watched getting a handle on constrain was utilized to gauge the forecast execution. Comes about appeared that arm developments had a critical effect on getting a handle on drive expectation execution. Inter-condition MADs were more prominent than intra-condition MADs.
Kieliba et al. [36], used EMG signal to measure the effect on weights of synergy and inter-subject similarity (ISS) by utilizing data of experimental of IS-muscles upon limb.
Liu et al. [38], considered with mechanical restoration that points in helping specialists amid delayed recovery handles. They utilized K-nearest neighbours (KNN) calculations to anticipate the user's expecting shifting heading, and the intuitively torque eyewitness moreover utilized to alter the energetic attitude of the robot exoskeleton to form it mobile and lighter. They connected that strategy to the dynamic control of recovery and exercises of day by day living (ADL) errands. They conducted an arrangement of tests, and the test comes about were very engaging.
Further work hoped to add more modes like ramp climbing and stair ascending. Wang et al., [15] proposed a hybrid control that uses EMG data from Gastrocnemius muscle with intrinsic controller on the prosthesis to (1) Control the gain of ankle command torque and (2) Control the transition between level-ground walking, stair ascend and descend. An amputee of bilateral, was worn a powered ankle prosthesis on a right leg and a passive prosthesis on the other (left). Gait patterns that were studied: Level-ground walking, stairs ascending and descending. Future work suggested more pre-processing of EMG input data to lessen motion artefacts. An independent-phase strategy was proposed in [23]. It tries to identify seven locomotion modes. Two Gluteal and nine residual Thigh muscles were investigated. Events of Gait were exposed by force-sensitive-resistor-based switches foot placed under the tested foot and using motion data of light reflective signs placed over the toe and heel. Synchronization of these signals is done. System was tested on EMG data collected from two subjects with transfemoral (above knee) amputations and eight non amputees' subjects. The study compared using two classifiers: Artificial Neural Network (ANN) &Linear Discriminant Analysis (LDA). The difference was not that significant. LDA is preferred to be used in further studies because it is easy to do without regularization parameter is considered. Classification accuracy is approximately 80% - 95%. The results suggest that the new independent-phase strategy could be used for neural-controlled artificial legs. Advances of this work were proposed in [24]. EMG Signals from two Gluteal muscles on the amputated side and the Thigh muscles of the residual limb were monitored. From 7 to 9 EMG electrodes were located on the outstanding limb based on the outstanding limb length. Measurements were also taken from ground reaction forces moments sensors. There are 5 of transitions mode and 6 locomotion modes were investigated. The different locomotion modes were represented in numerous actions i.e., level-ground walking, avoiding an obstacle, stair up/down, and ramp up/down. Support Vector Machine (SVM) gave better results than LDA as in this study longer gait phases were studied. Results also showed that it was harder to classify swing phase compared to classifying during Stance Phase.

This might be a result of little force/moment information existing during swing phase. Some data used in this study was not practical if used on daily basis for an amputee, for example, data from the sound (healthy) leg were measured, which would not be the case in real use of prosthesis. Therefore, further investigations were put in mind to gain information in another way.

Hargrove et al. studied flexing and extending the knee joint in [25]. Two unilateral transfemoral amputees and one bilateral amputee, with transfemoral amputation on one leg and transtibial on the other, performed the tests. In all situations, all matters were considered by a prosthetic knee, previously designed in [26], on one limb and an intact knee on the other. They were asked to move both their missing knee and the intact one like motions displayed on a computer screen. Surface EMG from the Hamstring and Quadriceps muscles of the residual limb were measured. Quadratic Discriminant Analysis (QDA) & LDA were used to classify the intent of the subjects to either ex or extend their knee joint. Based on a fivefold cross validation of classification accuracy, the QDA classification provided higher classification accuracies than LDA.

This study integrated with the approach in [18] studying level ground walking, standing and the transmission among stand and sit. In the previous study, one degree of freedom (DOF) was studied, Hargrove et al. in [27], had two tests, one with 2 DOF and the other with 4 DOF. Four transfemoral amputee participants and four non-amputees were recruited. Surface EMG electrodes were placed over nine muscles. Knee and ankle joints movement were studied. The motions investigated were extending and flexing Knee, dorsiflexion and plantar flexy, external, and internal rotation, internal and external femoral rotation, and relaxation. Participants replicated what they saw on a computer screen. A motion was made in a virtual environment, and they had to mimic it: how much time would the participant take to complete a motion and motion completion percentage (how many times the motion is done successfully). Future experiments were supposed to include real tests instead of the virtual environment that was used in this study.

The results indicate that there are five thigh residual muscles were requested to obtain accurate control. The system of pattern recognition was estimated on its classification accuracy and satisfying real-time need. Future studies would be to use neural information for weight bearing activities.

In [28] more amputee members were enlisted. Six subjects with one-sided transfemoral removals and six non-amputee subjects are taken an interest in this think about. The proposed control framework depended on data extricated from the signals of EMG to hold a lower appendage prosthesis Sagittal plane movements of the knee and lower leg could be precisely (90%) recognized and controlled in both a virtual environment and on an incited prosthesis transfemoral utilizing as it were EMG signals measured from nine leftover thigh muscles. The comes about appeared that as it were five remaining thigh muscles were required to attain precise control. The proposed framework was assessed on its classification precision and fulfilling real-time require. Future considers would be to utilize neural data for weight bearing exercises

Sensors are put on the prosthesis Reference Section

III. EMG Analysis and Classification Methods

A. Datasets

The developing of data analysis and machine learning requires a large amount EMG signal data. Over the last decade, there are a lot of EMG data sets are online and available to download. Most available EMG datasets are for upper limbs, forearms, and fingers [52-56]

For lower limbs, a benchmark for lower limb neuro-mechanical signals is represented by Encyclopedia of Able-bodied Bilateral Lower Limb Locomotors Signals (ENABL3S) [57]. The recorded signals are from 10 able-bodied people via sensors which *wearable among movement that is unassisted. In expansion to different movements: sitting* and standing, points openly transitioned between level ground strolling, incline up/down, and stair up/down at their self-selected speed. Points were reciprocally instruments with (EMG) surface from 7 lower appendage muscles, goniometers at the knee, lower leg (ankle), and thigh. Extra units of measurement were around the waist. Highlights frequently utilized in limbs which are lower expectation acknowledgment for controlling prosthesis is released from toe off stride occasions and windows close heel contact.

More dataset for EMG lower limb is presented from the machine learning repository (UCI) [58]. It incorporates 3 distinctive works out: sitting, standing and strolling within the muscles within the works out. It is recorded for twenty-two male subjects, eleven with distinctive knee variations from the norm already analyzed by a proficient. There are three movements for the behavior analysis related with the knee muscle, walk, and leg expansion from a descent position, and flexion of the leg ascent. These signals are acquired with 4 electrodes, namely, Vastus Medialis, biceps femoris, semitendinosus, and rectus femoris. Also, the electrodes are attached with the goniometer in the knee. However, data log gear was utilized MWX8 by Biometrics of eight computerized channels and four analog channels, of which four for sampling were utilized SEMG and one for goniometry, this information was obtained straightforwardly to the computer MWX8 inside microSD card capacity and in Real-time Data log computer program transmission through Bluetooth connector, 14-bit determination and examining recurrence of 1000Hz. The overall number of terminals is four, comparing to the time arrangement one for each channel (1:4). Each arrangement contains arounds five offers or movement redundancies for each subject.

B. Pre-processing

The fundamental stage is pre-processing EMG data for successful feature extraction and high accuracy classification [29]. Usually, sensed EMG data are amplified to increase the amplitude of the signal, where an amplification factor of approximately 1000 is done before sampling.

Huang et al. in [23], high pass filter is used and cut off frequency is 25 to eliminate artefacts motion from raw EMG signals. In [24], a pass –band filer is used to filter EMG signals, the range of frequency among 20 and 420 Hz and the gain is 1000.

In [30, 31, and 24], the filtered signals were sampled with rate between 1-2 kHz.

Keiliba et al. [36] used variable frequencies and normalization methods in filter cut-off to pre-process the EMG signals.

C, De-noising

EMG Signals are subject to noise caused by different sources. Signal denoising, therefore, is a fundamental step for further signal processing steps. Some of the various noise sources are:

1) Electrical noise generated from electrical equipment's. To eliminate this type of noise a trade-off between a suitable electrode size and at the same time get good signal quality is chosen to get low noise-to-signal ratio.

2) Electromagnetic noise located on the body surface. Continuously, the human body's Publication, Archiving and Indexing surface produces electromagnetic radiation.

The ambient noise is emerged from the source of power radiation at 60 hertz that is called power- line interference (PLI), which is happened from the varieties in the impedance of electrode and lost currents on the object. Signal can be cleaned from this by using Laguerre fitter. It has been shown to be more operative than other algorithms.

Fig. 4 shows a block diagram for noise removal proposed by Chowdhury et al. [32].

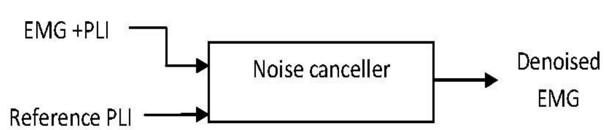

Fig. 4 General block diagram of PLI cancelling system [32].

3) Crosstalk noise. EMG signal from a group of muscle out of interest are considered as crosstalk noise, when recorded with the EMG signal of the muscle of interest. This noise polluted the signal and wrong interpretation of the information of the signal could be caused

4) Internal noise can be defined as the increased of the amount of fat in the body, which causes increasing in the separation among the sites detection and fibers of active muscle, and hence reduce the EMG signal quality. This type of noise is called the internal noise [32, 33].

D. Segmentation

EMG signal segmentation means to cut the input signals into disjoint sub-signals based on temporal or event-based criteria.

In event-based segmentation, the signal is divided into sub-signals based on events regarding the objectives of the following classification steps. Most probably the acquisition system is occupied by special sensors for event detection and synchronizing the event with EMG signal such as footswitch.

Huang et al in [23] is placed a force sensitive resistor under the foot tested, to detect events of Toe Off (TO) and Heel Contact (HC). The signals of EMG are then segmented to have complete gait cycles. The cyclic nature of EMG signals of gait EMG signals makes it easier in segmentation over other not cyclic EMG signals such as arm movements. This nature makes it easy to train locomotion classification systems with segments of gait modes between two HCs.

In temporal-based segmentation, the signal is divided into sub-signals each of which has a predetermined length or number of sample points. In [28], EMG signals were split using sliding window where window size is 250 ms which slides 50 ms allowing 200 ms to be kept on an overlapping.

Huang et al in [23] proposed second level of segmentation for training their system. They had four 200-ms segments of EMG signals: (1) Post-HC, (2) Pre-TO, (3) Post-TO and (4) Pre-HC, illustrated in Fig .5 GME, RF, VM, BFL, TA and GASL are abbreviations for lower limb muscles:

Rectus Femoris :RF,
Tibialis Anterior:TA,
Gluteus Medius :GME,
Gastrocnemius Lateral Head :GASL.
Vastus Medialis:VM,
Biceps Femoris Long head:BFL

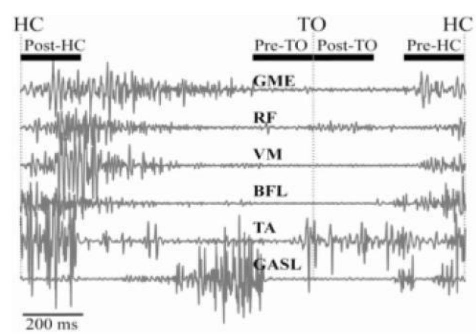

Fig. 5 Four defined phase windows aligned with Heel Contact (HC) and Toe-Off (TO) [23].

E. Classification

User intent recognition systems depend on classification techniques to identify the user of the prosthesis intention to control the prosthesis to help the user make minimal effort with comfort and safety.

Different research used Linear Discrimination Analysis LDA classifier. It is used in [23] to classify between seven modes walk on ground, ascend stairs, descend stairs, step over an obstacle turn and stand l. Hargrove et al [28] used LDA classifier to classify between non-weight bearing activities. In [34], it was mentioned that LDA increases the proportion variance class and minimizes the proportion within variance class. LDA gives similar performance for classification different types, it is very good for real-time control.

Salim et al., [37] used Autoregressive Moving Average – ARMA- parameters and the residual variance to distinguish between the well signals and myopathy signals of the skeletal muscle tissue. Their proposed framework used LDA classifier for the EMG signal dynamics to characterize it. Surprising enhancements in accuracy, sensitivity, and specificity were accomplished, which are higher values than previous records in the literature and offered an improved model for myopathy analysis.

Huang et al., [23] suggested a phase independent strategy where there are 4 classifiers, one for each sub-phase post-HC, pre-TO, post-TO and pre-HC as illustrated in Fig. 6.

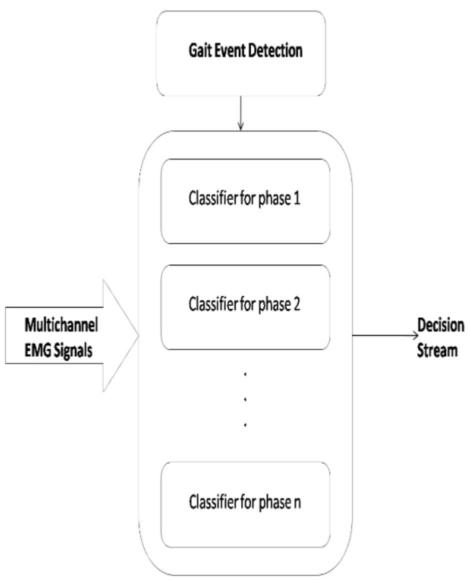

Fig. 6 Phase Independent Strategy as represented in [23].

In [23], more complex ANN classifier in addition to LDA is investigated. In [24], Support Vector Machine (SVM) gave better results than LDA and enabled longer gait phases were studied.

The authors in [38] applied the K-nearest neighbors (KNN) algorithm to know the moving direction prepared by the user. The extracted information is utilized to modify the behavior of an exoskeleton robot that made it move. Table 1 represents an outline of various techniques to classify EMG signal applied for different body parts. It also shows the achieved accuracies.

TABLE I

reflects some experiments with the classifiers, Random Forest, Principal Components Analysis, etc. The table proves that the classifiers gave high accuracy values for user intent recognition systems in different parts of the body

Author	*Classifier*	*Body part*	*Accuracy*
Liao, [59]	SVM (Support Vector Machine)	Arm	94%
Rekhi, [60]	Multi class-SVM	Forearm	96%
Futamata, [61]	SVM	Hand	4channel LSVM: 94.56% 4channel Non-LSVM: 93.33%
Zhang, [62]	Principal Components Analysis (PCA)	Hand	99.0% motion success rate 99.8% classification success
Yu, [63]	LDA	Arm-Full Limb	Full-limb EMG = 88.8±9.9% Forearm EMG = 90.3±4.2%
Negi, [64]	PCA / ULDA (uncorrelated linear discriminant analysis)	Upper limb	PCA range from (88.33430 ± 4.40186 - 95.85695 ± 0.96225) ULDA (89.81725 ± 3.40176 - 96.35613 ± 0.69265)
Champaty, [65]	Random Forest + Wavelet Transform	Sub-vocal region	90% when two features were considered 75% with five features
Ling-ling, [66]	Random Forest	Gluteus medius muscle & 5 main muscles of lower limb	99.2% in five movement modes recognition
Aydõn, [67]	KNN (k-nearest neighbours) & LDA	Prosthetic Fingers Control	81.6% for KNN 98.94% for LDA
Wan, [68]	KNN	Pre-defined hand gestures	96.05%
Praveen, [69]	KNN	Hand	92-94%
Hussein, [70]	ANN (Artificial neural network)	Muscle-Diseases	91%

OWEIS, [71]	ANN	HAND	88.4 %

F. Deep Learning Strategy for Classification and Feature Extraction

The deep learning [43] is a rising class of machine learning approaches for classification reason. It could be an extraordinary frame of learning, when a network is learned and is built characteristic of features from all neurons of hidden layer [44]. It decreases the power of the mental thinking for feature extraction [45]. The foremost broadly used profound learning strategy is the CNNs. It made up of convolution, pooling, dropout layers, and completely layers are connected. The fully connected layers were the same as the ordinary ANN [46].

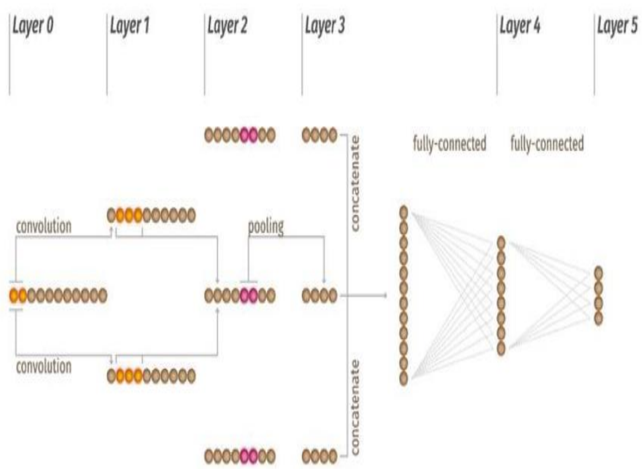

Fig. 7 CNN Structure as introduced in [44].

The authors in [49, 44, 50, 51, and 47] used the CNN in their experiments on EMG signals for classification of hand movement, Movement of intention decoding, recognition of gesture, guidance of robot arm and Neuroprosthesis control, respectively. They achieved 66.5, 99.5, 90, 99.7, and 83 % accuracy, respectively. The approaches of deep learning execute good with diverse and large datasets.

Discussion and Conclusions

In Gait Intent Recognition system, the sensors are put on the prosthesis. The EMG signal emitted from the sensors is firstly smoothed by RMS and normalized using MVC methods. Then the noises are eliminated such as: electrical, electromagnetic, crosstalk, or internal noises. Next, the EMG signals are segmented into dis-joint sub-signals. After that the features are extracted for well and quick classification.

However, the classification process is the most important step which determines the user of the prosthesis intention. Different classifiers are used for that purpose i.e., LDA, SVM, ANN, KNN, PCA, or Random Forest. From the survey, theses classifiers gave good results. Alternatively, the trendy feature extractor and classifier, deep learning, offered efficient results for user intent recognition systems of lower/upper limbs.

From the survey it is concluded that Gait Intent Recognition system gave very good results for neuro-controlled powered prosthesis. In case of weight-bearing activities like walking, stair ascend. etc, gait intent recognition systems that rely on both mechanical and EMG input gave better results than depending on only EMG data. However, in case of non-weight-bearing activities like flexing or extending the knee, while sitting, EMG input was really successful and gave encouraging results.

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