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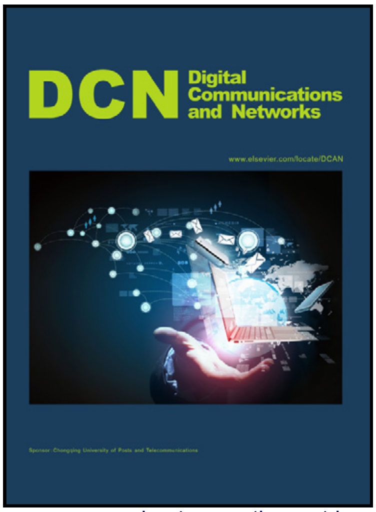

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Bio-signal based Control in Assistive Robots: A Survey

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Abstract

Recently, bio-signal based control has been gradually deployed in biomedical devices and assistive robots for improving the quality of life of disabled and elderly people, among which EMG (Electromyography) and EEG (Electroencephalography) bio-signals are being used widely. This paper reviews the deployment of these bio-signals in the state of art of control systems. The main aim of this paper is to describe the techniques used for: i) collecting EMG and EEG signals and diving these signals into segments (data acquisition and data segmentation stage), ii) emphasizing the important data and removing redundant data from the EMG and EEG segments (feature extraction stage), and iii) identifying categories from the relevant data obtained in the previous stage (classification stage). Furthermore, this paper presents a summary of applications controlled through these two bio-signals and some research challenges in the creation of these control systems. Finally, a brief conclusion is summarized.

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Keywords: Assistive Robots, EMG, EEG, Feature Extraction & Classification.

1. Introduction

As traditional assistive robotic systems and rehabilitation devices have a traditional user interface, such as joysticks and keyboards, many disabled people have difficulty in accessing them and more advanced hands-free human-machine interfaces become necessary. EMG (Electromyography signal: electrical activity generated during the

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contraction of a skeletal muscle) and EEG (Electroencephalography signal: electrical activity of the brain recorded from the scalp) are two kinds of bio-signals that are physical quantities which vary with time [1]. They contain rich information in which a user's intention in the form of a muscular contraction and a brainwave can be detected through surface electrodes. These detected bio-signals can be used in a control system to operate rehabilitation devices and robots.

In general, the development of EMG and EEG control systems can be divided into four stages [2-4], namely (1) data acquisition and data segmentation, (2) feature extraction, (3) classification and (4) controller. As shown in Fig. 1, the bio-signals are acquired from the human body and then filtered to reduce the noise produced by other electrical activities of the body or inappropriate contact of the sensors, namely artifact. At this first stage the output is raw signal. In the second stage, i.e. feature extraction stage, the raw signal obtained from the previous stage is converted into a feature vector. The feature vector represents relevant structure in the raw data. Then, a process called dimensionality reduction is carried out, in which redundant information is eliminating from the feature vector, generating a reduced feature vector [3]. The third stage is classification, i.e. translation algorithm, in which categories are identified from the reduced feature vector by employing pattern recognition techniques. Finally, in the fourth stage, i.e. the controller, the categories obtained from the classification stage are translated into control commands for execution.

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The most important advantage of bio-signal control systems over other types of control systems, such as body-powered mechanical systems, is its hands-free control a user's intention. For instance, bio-control is now a competitive alternative for mechanical body-powered systems in commercial functional prosthesis. It provides more proximal functions and cosmetic appearance [2]. Focusing on EMG and EEG signals, many potential real-

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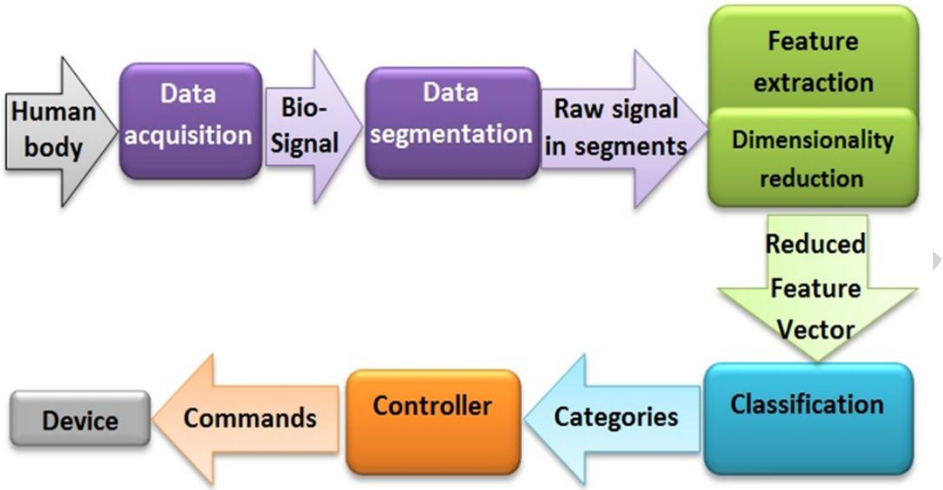
world applications operated through these two bio-signals have been reported, including multifunction prosthesis, intelligent wheelchairs, gait generation, grasping control, virtual keyboards, gesture-based interfaces, etc.

Figure 1 Stages for developing EMG and EEG control systems



The rest of the paper is organized as follows. Section 2 presents the stage of data acquisition and data segmentation. Then Sections 3 and 4 explain the feature extraction stage, and the classification stage, respectively. Section 5 outlines some applications of EMG and EEG control systems. Section 6 provides some research challenges in the development of EMG and EEG control systems. Finally, a brief conclusion is given in Section 7.

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2. Data acquisition and segmentation

Once the EMG signals are gathered from muscles or EEG signals are collected from the scalp, they are divided into representative segments to extract features from each one. A general overview of the data acquisition and data segmentation stage can be seen in Fig. 2.

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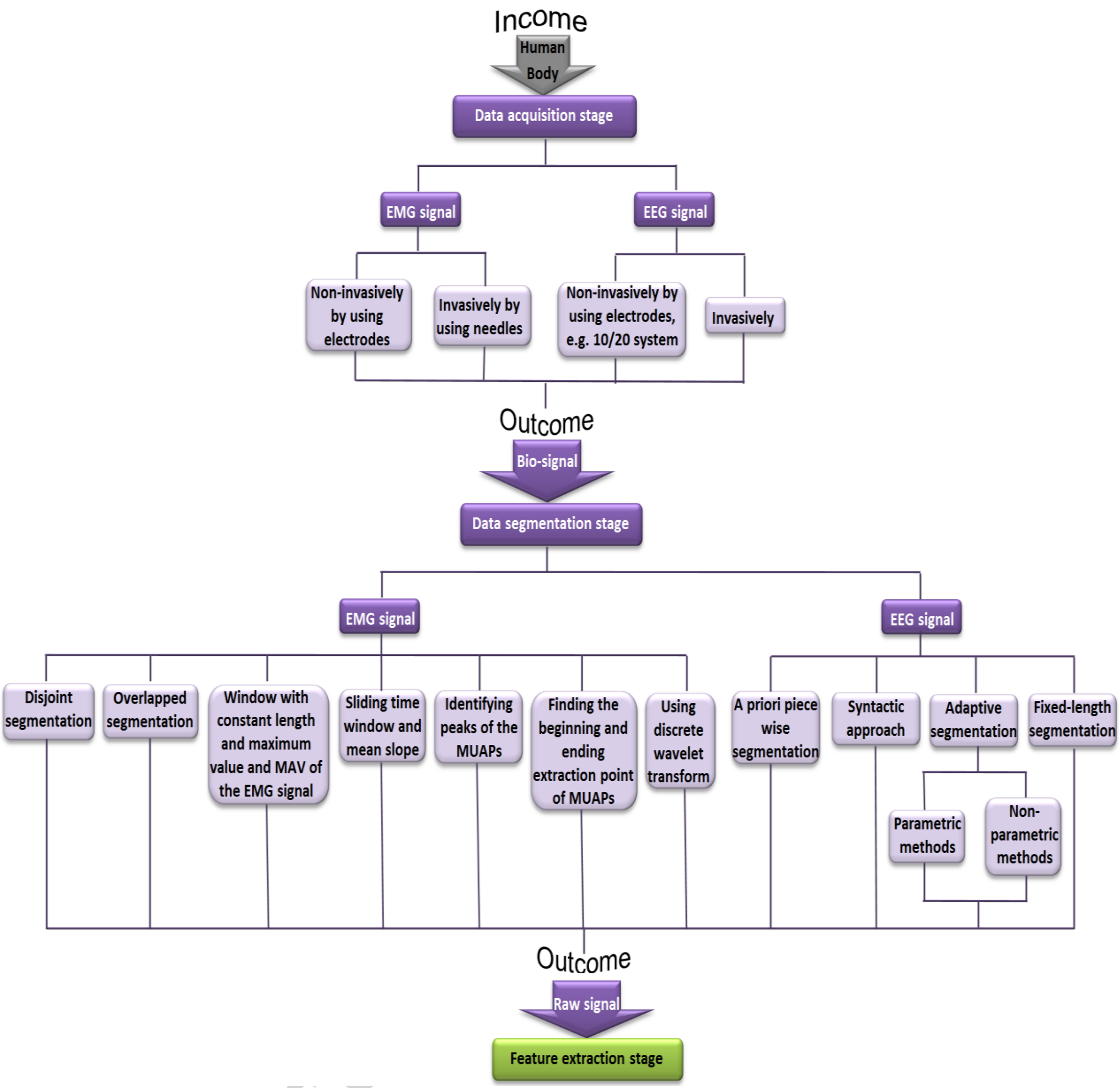
Figure 2 Overview of the data acquisition and data segmentation stage



2.1. EMG data acquisition and segmentation

In general, myoelectric activities can be acquired by two techniques [5]: (i) invasively by inserting a needle electrode through the skin directly into the muscle; or (ii) non-invasively by placing a surface electrode on the skin overlying the muscle. The spatial resolution of the non-invasive data acquisition technique is more limited than the invasive data acquisition technique, therefore the high frequency content of a MUAP (Motor Unit Action Potential) is smoothed when the EMG signal is collected non-invasively.

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To segment EMG signal, Christodoulou and Pattichis employed a fixed length window and a segmentation algorithm that calculates a threshold depending on the maximum value and the mean absolute value of the whole EMG signal [6]. Peaks over the calculated threshold are considered as candidate segments. On the other hand, Gut and Moschytz used a sliding time window to determine the beginning and the end of a segment [7]. If the mean slope within this window exceeds a certain threshold, the beginning of a segment is detected; while the end of a segment is reached when the total variation of the EMG within the window falls below another threshold.

Both disjoint and overlapped segmentation methods have been evaluated by Oskoei and Hu [8]. In disjoint segmentation, separate segments with a predefined length are used for feature extraction; while in overlapped segmentation, the new segment slides over the current segment with an increment. Therefore, disjoint segmentation is associated with segment length, while overlapped segmentation is associated with length and increment. They compared classification performances over disjoint segments with a length of 200ms and overlapped segments with a length of 200ms and an increment of 50ms. Their results showed that a disjoint segmentation with a length of 200ms provides high performance during EMG classification and a reasonable response time to allow real-time application; whereas overlapped segmentation with a length of 200ms and an increment of 50ms shortens the response time without a noticeable degradation in accuracy.

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Conversely, Kaur et al. [9] analyzed three EMG segmentation techniques: 1) by identifying the peaks of the MUAPs (Motor Unit Action Potentials), 2) by finding the beginning extraction point (BEP) and ending extraction point (EEP) of MUAPs, and 3) by using discrete wavelet transform (DWT). In the first technique, the EMG signal is segmented by detecting areas of low activity and candidate MUAPs; the second technique identifies the BEPs and EEPs of the possible MUAPs by sliding a window throughout the signal; and in

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the third technique, EMG signal is decomposed with the help of daubechies4 (db4) wavelet to detect MUAPs. In general, the first technique reported the best performance with a total success rate of 95.90%, in comparison with the total success rates of 75.39% and 66.64% for the second and third techniques, respectively.

2.2. EEG data acquisition and segmentation

The most used recording technique for clinical EEG and for the study of event related potentials in non-clinical settings is the International 10/20 system; which is a standardized system for electrode placement proposed by Jasper [10]. This system employs 21 electrodes attached to the surface of the scalp at locations defined by certain anatomical reference points. The numbers 10 and 20 are percentage signifying relative distances between different electrode locations on the skull perimeter. The sampling rate for EEG signal acquisition is usually selected to be at least 200Hz [5].

To segment EEG signal, Biscay et al. deployed three methods [11]: (1) adaptive segmentation, which is based on the detection of changes of an auto-regressive model; (2) a priori piece-wise segmentation followed by clustering; and (3) the syntactic approach, which incorporates grammatical rules with the temporal contextual information for segmentation.

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On the other hand, Kaplan et al. used two approaches to segment EEG signals [12]: fixed-length segmentation and adaptive segmentation. The fixed-length segmentation consists of four stages: (a) first, the EEG recording is divided into equal minimal (‘elementary’) segment lengths; (b) then, each segment is characterized by a certain set of features (e.g., spectral estimations or auto-regressive coefficients); (c) the main EEG segments are assigned to one of a number of classes accordingly to their characteristics by using one of the multivariate statistical procedures; and finally, (d) the boundaries between the

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segments belonging to a same class are erased. Each of these stationary segments is characterized by its specific duration and typological features, but some EEG fragments contain transition processes and, are not strictly stationary, since this segmentation approach does not take into account the properties of the EEG recording. In contrast, adaptive segmentation splits the EEG recording into quasy-stationarity segments of variable length [13]. This process can be done by employing parametric methods and non-parametric methods.

Parametric methods describe the piecewise stationary structure of the EEG signal adequately, and are effective if the phenomenological model of the process under study is known [14][15]. Dvořák and Holden [16] established auto-regressive model (AR), autoregressive moving average (ARMA) and Kalman filter, as the most used parametric methods for EEG signal analysis. However, a drawback is that all these methods designed for the analysis of non-stationary processes are based on a procedure which may be applied only to stationary processes [12]. In this context, Aufrichtig et al. [17] examined the parametric method called AR model for segmenting EEG signals in four manners: (a) an AR-model is estimated for the reference window and the signal in the moving window is filtered with the corresponding inverse filter; (b) an AR model is estimated for the moving window, followed by an inverse filtering and calculation of test statistic for the reference window; (c) an asymptotic Gaussian distribution of the AR-parameters is used to achieve a test statistic for the difference between the AR-parameters of the reference and moving windows; and (d) a sum of two statistical tests is calculated, one statistical test corresponds to the difference between the AR-parameters of the reference and moving windows, and the other statistical test is the same difference, but the order of the windows is inverted, an asymptotic Gaussian distribution of AR-parameters is used in both differences.

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Non-parametric methods do not make numerous or stringent assumptions about the population (EEG recording), and do not need a priori information about probability distributions of random sequences [12, 18]. Brodsky et al. [15] proposed a non-parametric method for the segmentation of the EEG signal called the algorithm of change-point detection. This consists of five steps: (a) construction of the diagnostic sequence (a random sequence of detection of changes) from an initial signal, (b) checking the homogeneity hypothesis, (c) preliminary estimation of change-points, (d) rejecting doubtful change-points, and (e) final estimation of change-points.

3. Feature extraction

The feature extraction stage involves the transformation of raw signal into a feature vector by reducing noise and highlighting important data. This stage implies “dimensionality reduction”, i.e. eliminating redundant data from the feature vector. An overview of this stage can be found in Fig. 3.

3.1. EMG feature extraction

Three types of features are used in EMG control systems [3]: (a) time domain features, (b) frequency domain features, and (c) time-frequency domain features. The time domain features are computed based on signal amplitude. The resultant values give a measure of waveform amplitude, frequency and duration within some limited parameters [19]. On the other hand, frequency domain features are based on signal’s estimated power spectrum density (PSD) and are computed by periodogram or parametric methods; but these features in comparison with time domain features require more computation and time to be calculated [19]. The time-frequency domain features can localize the energy of the signal in time and frequency, allowing a more accurate description of the physical phenomenon;

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but these features generally require a transformation that could be computationally heavy [20-21]. The features of all above domains are presented in tables 1 and 2.

Figure 3 Overview of the feature extraction stage

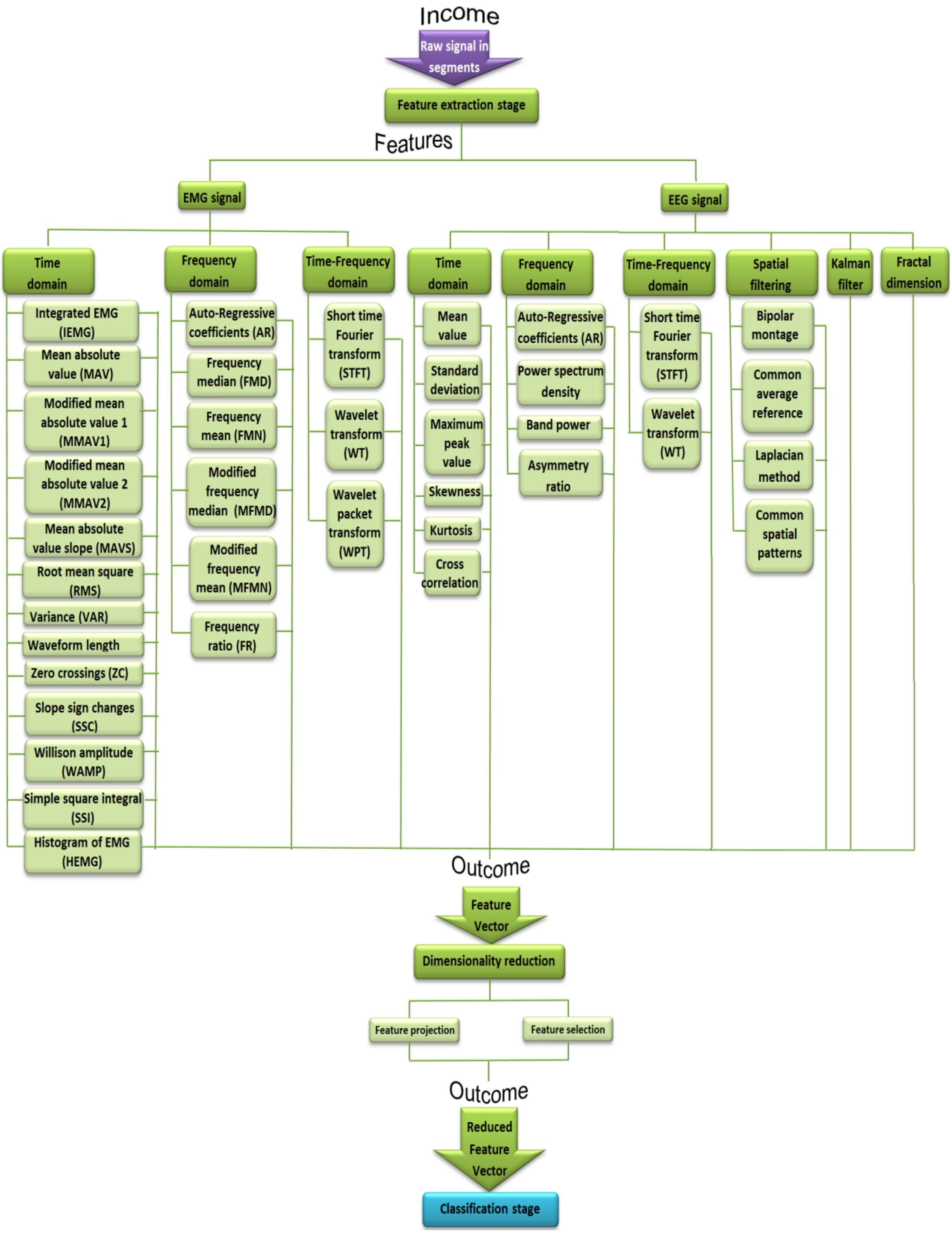

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Table 1
EMG time domain features.

Time domain features			
Integrated EMG (IEMG), [22]	$IEMG_k = \sum_{i=1}^{N} \lvert x_i \rvert$	*Root Mean Square (RMS), [24]*	$RMS_k = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_i}^2}$
Mean Absolute Value (MAV), [23]	$\mathrm{MAV_k} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \lvert \mathrm{x_i} \rvert$	*Zero Crossings (ZC), [23]*	ZC is incremented, if $\{x_i > 0\, and\; x_{i+1} < 0\}\, or$ $\{x_i < 0\; and\; x_{i+1} > 0\}$ $and\quad \lvert x_i - x_{i+1} \rvert \geq \epsilon$
Modified Mean Absolute Value 1 (MMAV1), [24]	$MMAV1_k = \frac{1}{N}\sum_{i=1}^{N} w_i \lvert x_i \rvert$ $w(i) = \begin{cases} 1, & 0.25N \leq i \leq 0.75N \\ 0.5, & otherwise \end{cases}$	*Slope Sign Changes (SSC), [23]*	SSC is incremented if $\{x_i > x_{i-1}\; and\; x_i > x_{i+1}\}\, or$ $\{x_i < x_{i-1}\, and\; x_i < x_{i+1}\}$ $and\, \lvert x_i - x_{i+1} \rvert \geq \epsilon\; or$ $\lvert x_i - x_{i-1} \rvert \geq \epsilon$
Modified Mean Absolute Value 2 (MMAV2), [24]	$MMAV2_k = \frac{1}{N}\sum_{i=1}^{N} w_i \lvert x_i \rvert$ $w(i) = \begin{cases} 1, & 0.25N \leq i \leq 0.75N \\ \frac{4i}{N}, & 0.25N > i \\ \frac{4(i-N)}{N}, & 0.75N < i \end{cases}$	*Willison Amplitude (WAMP), [24]*	$WAMP_k = \sum_{i=1}^{N-1} f(\lvert x_i - x_{i+1} \rvert)$ $f(x) = \begin{cases} 1, & x > \epsilon \\ 0, & otherwise \end{cases}$
Mean Absolute Value Slope	$MAVS_k = MAV_{k+1} - MAV_k$	*Simple Square Integral (SSI), [24]*	$SSI_k = \sum_{i=1}^{N} \left(\lvert {x_i}^2 \rvert \right)$

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(MAVS), [24]			
Variance (VAR), [19]	$VAR_k = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2$	*Histogram of EMG (HEMG), [24]*	HEMG divides the elements in EMG signal into *b* equally spaced segments and returns the number of elements in each segment
Waveform Length (WL), [23]	$WL_k = \sum_{i=1}^{N-1}\left\|x_{i+1} - x_i\right\|$		

Variables of the time domain features

x_i is the value of each part of the segment *k*.

N is the length of the segment.

$\bar{x}$ is the mean value of the segment *k*.

$\in$ is a threshold.

Table 2

EMG frequency and time-frequency domain features**.**

Frequency domain features		*Time-frequency domain features*	
Auto-Regressive coefficients (AR), [24]	$x_k = \sum_{i=1}^{N} a_i\, x_{k-i} + e_k$	*Short Time Fourier Transform (STFT), [26]*	$STFT_x\left(t,w\right) = \int W^*(\tau - t)x(\tau)e^{-j\omega\tau}d\tau$
Frequency Median (FMD), [19]	$F_{MD} = \frac{1}{2}\sum_{i=1}^{M} PSD_i$		
Frequency Mean (FMN); [19]	$F_{MN} = \frac{\sum_{i=1}^{M} f_i PSD_i}{\sum_{i=1}^{M} PSD_i}$ *f_i = (i * $sampling_{rate}$) / (2 * M)*	*Wavelet Transform (WT), [1]*	$W_x\left(a,b\right) = \int x\left(t\right)\left(\frac{1}{\sqrt{a}}\right)\psi^*\left(\frac{t-b}{a}\right)dt$
Modified Frequency Median (MFMD), [24]	$MFMD = \frac{1}{2}\sum_{j=1}^{M} A_j$		
Modified Frequency Mean (MFMN), [24]	$MFMN = \frac{\sum_{j=1}^{M} f_j A_j}{\sum_{j=1}^{M} A_j}$	*Wavelet Packet Transform*	WPT is a generalized version of the continuous wavelet transform and the discrete wavelet transform [3]. The basis for the WPT is chosen

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Frequency Ratio (FR), [25]	$FR_j = \frac{\left\| F\ (^2) \right\|_{jlowfreq}}{\left\| F\ (^2) \right\|_{jhighfreq}}$	*(WPT)*	using an entropy-based cost function [27].

Variables of the frequency domain features	*Variables of the time- frequency domain features*
a_i is AR coefficients. e_k is white noise or error sequence. M is the length of the power spectrum density. PSD_i is the i^{th} line of the power spectrum density. A_j is the EMG amplitude spectrum at frequency bin *j.* f_j is the frequency of the spectrum at frequency bin *j.* $\left\| F\ (^2) \right\|_j$ is the fast Fourier transform of EMG signal in channel *j.* *lowfreq* is the low frequency band. *highfreq* is the high frequency band.	*W(t)* is the window function. * is the complex conjugate. τ represents time. w stands for frequency. *x(t)* is the function representing the input signal. ψ^* is the complex conjugate of the mother wavelet function. $\psi^*\left(\frac{t-b}{a}\right)$ is the shifted and scaled version of the wavelet at time b and scale a.

Several studies have assessed the performances of these EMG features (e.g. Huang and Chen [22], Oskoei and Hu [19], Phinyomark et al. [24]). Huang and Chen [22] have carried out a comparison of the performances of EMG time domain features (IEMG, VAR, bias zero crossings (BZC), SSC, WL and WAMP) and EMG frequency domain features (AR of order four) in two stages, in order to distinguish hand movements. In the first stage, they applied the Davies-Bouldin index to evaluate each feature, resulting that VAR, WL and IEMG reported better cluster separability than others. In the second stage, the best features (VAR, WL and IEMG) obtained in the previous stage were combined with other features (WAMP, BZC and AR of second order) to reinforce the whole clustering performance. From the results, two combinations of features were used in the neural network classification engine. On the other hand, Oskoei and Hu [19] applied advanced subset search algorithms rather than comparing index to evaluate EMG features of upper limb. These algorithms consist of: (i) a genetic algorithm adopted as the search strategy; (ii) Davies Bouldin index and Fishers linear discriminant index employed as the filter

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objective functions, and (iii) linear discriminant analysis used as the wrapper objective functions. An artificial neural network was implemented as the classifier in the upper limb EMG system.

Phinyomark et al. [24] compared eighteen time domain features and five frequency domain features in a noisy environment, with the aim of determining which one has a better tolerance of white Gaussian noise. Their results showed that from the point of view of white Gaussian noise, MFMN was the best feature comparing with others on the quality of the robustness of EMG features. MFMN obtained an average error of 6% on strong EMG signals and 10% on weak EMG signal at signal-to-noise ratio 15 value of 0dB. Also, MFMN reported an average error of 0.4% in both strong and weak EMG signals at signal-to-noise ratio value of 20dB.

Table 3

EEG time and frequency domain features.

Time Domain Features		*Frequency Domain Features*	
Mean Value	$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$	*Auto-Regressive coefficients (AR)*	As can be seen in [32 - 34], this feature is used in EEG signal as well as in EMG signal.
Standard deviation	$x_{std} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}}$		
Maximum peak value, [28]	$x_k = \max\lvert x_i \rvert$	*Power spectrum density (PSD), [35]*	$PSD = \left\lvert \sum_{i=0}^{N-1} x_i e^{\frac{-j2\pi ki}{N}} \right\rvert^2$
Skewness. It measures the degree of deviation from the symmetry of a normal or Gaussian distribution. This measure has the value of zero when the distribution is completely symmetrical and assumes some nonzero value when the EEG waveforms are asymmetrical with respect to the baseline [29].			

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$$S_{k_{mc}} = \frac{\sum_{i=1}^{N} \frac{\left(x_i - \bar{x}\right)^3}{N}}{\left[\sum_{i=1}^{N} \frac{\left(x_i - \bar{x}\right)^2}{N}\right]}$$

Kurtosis. It reveals the peakedness or flatness of a distribution. In clinical electroencephalography, when EEG with little frequency and amplitude modulation is analyzed, negative values of kurtosis are observed; whereas high positives values of kurtosis are present when the EEG contains transient spikes, isolated high-voltage wave group, etc. [29]	$K_{mc} = \frac{\sum_{i=1}^{N} \frac{\left(x_i - \bar{x}\right)^4}{N}}{\left[\sum_{i=1}^{N} \frac{\left(x_i - \bar{x}\right)^2}{N}\right]^2} - 3$	*Band power*	Based on [33, 35], EEG contains different specific frequency components, which carry the discriminative information. This type of feature reflects the energy in several bands (α, β, δ, γ and θ). Once that the bands are filtered, the power spectrum density can be applied to each one to obtain important features.
Cross correlation. It measures the extent of similarity between two energy signals [30]. Chandaka et al. [31] explain that if a signal is correlated with itself, the resulting sequence is called the auto correlation sequence. The order of the subscripts, with *x* preceding *y,* indicates the direction in which one sequence is shifted, relative to other.	The cross correlation of *x(n)* and *y(n)* is given by: $\hat{R}_{xy}(m) = \begin{cases} \sum_{n=0}^{N-m-1} x_{n+m} y_n & m \geq 0 \\ \hat{R}_{yx}(-m) & m < 0 \end{cases}$	*Asymmetry ratio PSD, [36]*	$AS_{PSD} = \left[\frac{PSD_1 - PSD_2}{PSD_1 + PSD_2}\right]$

Variables of the time domain features	*Variables of the frequency domain features*
x_i is time series for $i = 1, 2, \ldots, N$. N is the number of data points. $\bar{x}$ *is the mean value.* *x(n)* and *y(n)* are two signal sequences, each of which with	$k = 0, 1, \ldots; N - 1$, N is the length of the EEG data. x_i represents the discrete samples of EEG signal. PSD_1 is the power spectrum density in one channel.

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a finite energy. m = …-2, -1, 0, 1, 2,…, represents the time shift parameter. Subscript xy stands for sequences being correlated.	PSD_2 is the power spectrum density in another channel, but in the opposite hemisphere.

3.2. EEG feature extraction

Since the EEG signal contains different waves, such as α, β, δ, γ and θ, the following methods are deployed in EEG feature extraction.

1) Time domain: These features are derived directly from the signal and include the (averaged) time-course. These features are summarized in table 3.
2) Frequency domain: These features characterize the power of the brain signal in several frequency bands. They are also presented in table 3.
3) Time-Frequency domain: These features describe how spectrum power varies over time. The short time Fourier transform and the Wavelet transform are the most employed.
4) Spatial filtering: This type of filtering uses signals from multiple electrodes to focus on activity at a particular location in the brain.
   - Bipolar montage - Bipolar channels are computed subtracting the signals from two neighboring electrodes [37].
   - Common average reference - This technique subtracts the average value of the entire electrode montage (the common average) from that of the channel of interest [38].
   - Laplacian method - It calculates for each electrode location the second derivative of the instantaneous spatial voltage distribution. The value of the Laplacian at each electrode location is calculated by combining the value at that location with the values of a set of surrounding electrodes. The distances to the set of surrounding electrodes determine the spatial filtering characteristics of the Laplacian [38].

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- Common spatial patterns - It is a technique to analyze multi-channel data based on recordings from two classes (tasks). It is given by:

  x_{CSP} (t) = x(t) W

  where x(t) is the signal, and W is a matrix that projects the signal in the original sensor space to a surrogate sensor space x_{CSP} (t). Each column vector of a W is a spatial filter. CSP filters maximize the variance of the spatially filtered signal under one task and minimize it for the other task [37].

Other complex methods have been used in EEG feature extraction, such as Kalman filtering [39], entropy, and fractal dimensions [33].

Some studies have evaluated the performances of various EEG features. Omidvarnia et al. [39] compared the features of AR, power of signal in different EEG bands (α, β, δ, γ and θ), wavelet coefficients and Kalman filter. Bayesian with a Gaussian kernel, Parzen estimation, K-nearest neighbor and back-propagation neural network were employed as the classifiers of the features. Kalman filter obtained the best performance over the other features when Parzen estimation, K-nearest neighbor and back-propagation neural network were used; while AR reported a better performance than Kalman filter when Bayesian with a Gaussian kernel was used. Likewise, Sabeti et al. [33] assessed the performances of the features of AR, band power, fractal dimension (calculated by Katz's, Higuchi and Petrosian methods) and wavelet energy, in order to determine the most relevant features for EEG signal classification of schizophrenic patients. The features were classified by using linear discriminant analysis and support vector machines. As a result the most consistent feature for discrimination of the schizophrenic patients and control participants was AR.

3.3. Dimensionality reduction

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Once the feature vector is obtained, it is necessary to reduce its dimensionality by eliminating the redundant data from it. The resulting vector is called reduced feature vector. There are two main strategies for dimensionality reduction [20]:

1) Feature projection - This strategy is to determine the best combination of the original features to form a new feature set, generally smaller than the original one [3]. Principal component analysis (PCA) can be used as a feature projection technique. PCA produces an uncorrelated feature set by projecting the data onto the eigenvectors of the covariance matrix [40].
2) Feature selection - This strategy chooses the best subset of the original feature vector according to some criteria for judging whether one subset is better than another. The ideal criterion for classification should be the minimization of the probability of misclassification, but generally simpler criteria based on class separability are chosen [3].

Englehart et al. [21] compared PCA as a feature projection technique and Euclidean distance class separability (CS) as a feature selection technique. The result was that PCA provided more effective means of dimensionality reduction than feature selection by CS, when time-frequency feature sets were employed.

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4. Classification

Once the features have been extracted from the raw signal (feature extraction) and the features with redundant information have been reduced (dimensionality reduction), some classifiers should be deployed to distinguish different categories among the reduced feature vector. Then, these obtained categories are going to be used in the next stage as control commands, i.e. the controller. As can be seen in Fig. 4, several techniques are deployed to classify data, e.g., neural networks (NN), Bayesian classifier (BC), fuzzy logic

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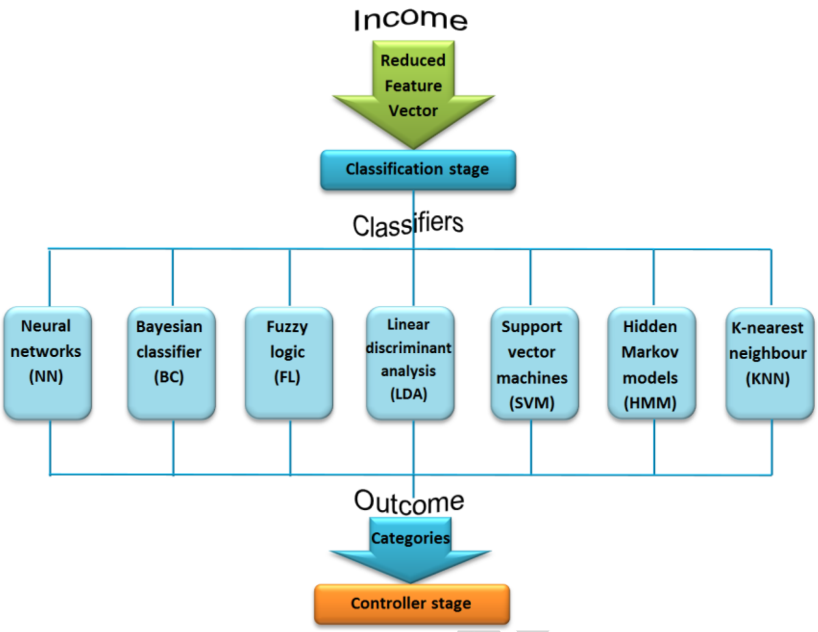
(FL), linear discriminant analysis (LDA), support vector machines (SVM), hidden Markov models (HMM) and K-nearest neighbor (KNN).

Figure 4 Overview of the classification stage



Nevertheless, before classifying EMG and EEG signals, it is important to bear in mind that these signals are expected to present variations in the value of a particular feature. Oskoei and Hu [2], explain that there are external factors, such as changes in electrode position, fatigue, and sweat that cause changes in a signal pattern over time. Besides, according to [2], a classifier should meet the following requirements to categorize EMG and EEG signals properly: i) it should be able to cope with varying patterns optimally; ii) it should prevent over fitting; and iii) it should be adequately fast, in order to meet real-time constraints.

4.1. Neural networks (NN)

A significant amount of literature presents the success of neural networks in bio-signal classification. The advantage of a neural network is its ability to represent both linear and non-linear relationships, and learn these relationships directly from data being modeled. It

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also meets real time constraints, which are an important feature in control systems [2]. Huang and Chen [22] developed a myoelectric discrimination system for a multi-degree prosthetic hand. They classify eight types of hand movements, such as three-jaw chuck, lateral hand, hook grasp, power grasp, cylindrical grasp, centralized grip, flattened hand and wrist flexion. They employ a back-propagation neural network (BPNN) for discriminating among the feature sets. One hidden layer and one output layer are used in the BPNN. The transfer functions for hidden layer neurons and output layer neurons are all nonlinear sigmoid functions. The discrimination system achieved success rates of 85% for offline test and of 71% for online test.

Also, Karlik [41] classified EMG signals for controlling multifunction prosthetic devices by using a three-layered BPNN. The inputs of the BPNN are auto-regressive (AR) parameters of a1, a2, a3, a4 and signal power obtained from different arm muscle motions. The result was an accuracy rate of 97.6% for categorizing six movements (R: resting, EF: elbow flexion, EE: elbow extension, WS: wrist supination, WP: wrist pronation and G: grasp) in 5000 iterations. Tsuji et al. [42] proposed a neural network, called "recurrent log-linearized Gaussian mixture network (RLLGMN)" for classification of time series, more specific for EEG signal. The structure of this network is based on a hidden Markov model (HMM). R-LLGMN can be interpreted as an extension of a probabilistic neural network using a log-linearized Gaussian mixture model, in which recurrent connections have been incorporated to make temporal information in use.

Chu et al. [43] proposed a real-time EMG pattern recognition for the control of a multifunction myoelectric hand from four channel EMG signals. To extract a feature vector from the EMG signal, they use a wavelet packet transform. For dimensionality reduction and nonlinear mapping of the features, they propose a linear-nonlinear feature projection composes of PCA and a self-organizing feature map (SOFM). The classification of the

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feature vector is carried out through a multilayer perceptron (MLP) with the following layers: a) an input layer constructed from the eight outputs of the SOFM for four channels; b) two hidden layers, each hidden layer with nine neurons; and c) an output layer with nine neurons for the nine hand motions to be recognized. The average classification success rates of the MLP were 97.024% when PCA+SOFM were used, 97.785% when SOFM was applied, and 95.759% when PCA was employed.

Subasi et al. [44] compared BPNN and wavelet neural networks (WNN) for classifying neuromuscular disorders of EMG recordings. They use an auto-regressive (AR) model of EMG signal as an input to classification system. The BPNN is designed with AR spectrum of EMG signal in the input layer, and an output layer of three nodes representing normal, myopathic or neurogenic disorders. On the other hand, the WNN is implemented with mono-hidden-layer forward neural network with its node activation function based on dyadic discrete Morlet wavelet function. A total of 1200 MUPs (Motor Unit Potential) obtained from 7 normal subjects, 7 subjects suffering from myopathy and 13 subjects suffering from neurogenic disease were analyzed. The success rates were: 90.7% for the WNN technique and 88% for the BPNN technique.

4.2. Bayesian classifier (BC)

Bayes classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong independence assumptions between the features. Bu et al. [45] developed an EMG control system, in which a robotic arm is able to imitate a sequence of arm motions created by a subject to carry out a task. A Bayesian network (BN) is used to predict the arm motion to be executed by the robotic arm based on the context information of the task. Besides the motion prediction, EMG signal is simultaneously classified by a log-linearized Gaussian mixture network (LLGMN). Then, the probabilities, which are outputs of LLGMN and the BN, are combined to generate

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motion commands. Experiments were conducted with four subjects, which executed the same task. The classification rates of using only the LLGMN and the proposed (BN with LLGMN) method were 85.1% and 92.9%, respectively.

4.3. Fuzzy Logic (FL)

There are many advantages of using fuzzy logic for bio-signal classification since bio-signals are not always strictly repeatable. Fuzzy systems are able to discover patterns in data that are not easily detectable. Fuzzy approaches exploit tolerance of imprecision, uncertainty, and partial truth, to achieve tractable, robust, and low-cost solutions for classification. Si et al. [46] designed an expert system for the pediatric intensive care unit with the aim of alerting experts about the level of abnormality of the EEG of the patients. They use fuzzy logic and neural networks to classify the data in the expert system. Four fuzzy sets are used for the amplitude of the EEG: severe, moderate, mild and normal. Results showed an accuracy percentage of 91%.

James et al. [47] developed a multi-stage system for automated detection of epileptiform activity in the EEG; using fuzzy logic and an artificial neural network called organizing feature map (SOFM). SOFM is in charge of assigning a probability value to incoming candidate epileptiform discharges (ED), while fuzzy logic is employed to incorporate spatial contextual information in the detection process of ED. Results showed that the system has a selectivity of 82%.

Ajiboye and Weir [48] presented a heuristic fuzzy logic approach to multiple EMG pattern recognition for multifunctional prosthesis control. Mean and standard deviation are used for membership function construction and fuzzy c-means (FCMs) data clustering is employed to automate the construction of a simple amplitude-driven inference rule base. The multi input-single-output fuzzy system consists of three parts: 1) input membership functions that convert numerical inputs to linguistic variables; 2) an inference rule base,

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which applies pattern classification to linguistic variables in order to obtain linguistic outputs and associated degrees of truth; and 3) an output membership function that defuzzifies the linguistic outputs by converting them to one numerical value. Four fuzzy sets are defined for signal gradation (OFF, LOW, MED, HIGH). Fuzzy -means (FCM) clustering is used to generate the rules. Overall classification rates ranged from 94% to 99%.

4.4. Linear Discriminant Analysis (LDA)

LDA is a well-known method for feature extraction and dimension reduction. It has been widely used in many bio-signal classification tasks such as brain tissue analysis, face and speech recognition. Sabeti et al. [33] analyzed EEG signals of 20 schizophrenic patients and 20 age-matched control participants using 22 channels, with the aim of determining the most informative channels to distinguish the two groups. Bi-directional search and plus-L minus-R Selection (LRS) are employed to select the most informative channels; while LDA and support vector machines (SVM) are used as classifiers. The results were accuracy rates of 84.62% for LDA, and 99.38% for SVM when bidirectional search was employed; and 88.23% for LDA, and 99.54% for SVM when LRS technique was applied.

4.5. Support Vector Machines (SVM)

The SVM is a kernel-based approach and has become an increasingly popular tool for machine learning tasks involving classification and regression. It has recently been successfully applied to bio-signal classification. Yom-Tov and Inbar [34] designed a classifier combining a genetic algorithm and support vector machines (SVM) to distinguish between movements of contralateral fingers using movement-related potentials embedded in EEG. Their results showed that, it is possible to select as few as 10 subject-specific features and achieves average accuracy rates of 87% between two limbs and 63% between three limbs. Crawford et al. [49] developed a 4-degrees-of-freedom robotic arm.

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They employ linear SVM as the classifier, achieving accuracy rates of 92-98% in 3 subjects.

Halder et al. [50] proposed a combination of blind source separation and independent component analysis (signal decomposition into artifacts and non-artifacts) with SVM (automatic classification). The accuracy percentages of the classification between artifacts and non-artifacts were 99.39% for eye blink, 99.62% for eye movement, 92.26% for jaw muscle, and 91.51% for forehead. Choi and Cichocki [51] controlled a motorized wheelchair online. They use the linear SVM to classify the feature vector obtained from the EEG signal into each class of motor imagery. Three subjects participated in the experiments; each one was asked to think of moving the hand and foot according to the direction of an arrow displayed on the computer.

Firoozabadi et al. [52] developed a hands-free control system for operating a virtual wheelchair, which is based on forehead multi-channels bio-signals. SVM is used to classify the motion control commands (forward, left, right, backward and stop). Three subjects (one adult and two children) participated in controlling a virtual wheelchair using the interface software on a personal computer. The accuracy percentages of SVM classification were: 100% for the adult, and 89.75% and 97.49% for the two children. Lucas et al. [53] proposed a multi-channel supervised classification of EMG signals to control myoelectric prostheses. The classification of six hand movements is performed with SVM approach in a multi-channel representation space. The results showed an average misclassification rate of 5%.

Oskoei and Hu [8] evaluated the application of SVM to classify upper limb motions using EMG signal. Four popular kernels were examined: radial-basis, linear, polynomial and sigmoid. The four applied kernels performed similarly. The average accuracy for all kernels was approximately 95.5 ± 3.8%. Gurmanik et al. [54] proposed an integrated binary SVM

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classifier to distinguish neuromuscular disorders by means of EMG signal. SVM aims to find optimal hyperplane for separating MUAP clusters. They use threshold technique to segment EMG signal and autoregressive coefficients (AR) as features. A total of 12 EMG signals obtained from 3 normal, 5 myopathic and 4 motor neuron diseased subjects were analyzed. The classification accuracy of binary SVM with AR features was of 100%.

Subasi and Gursoy [55] developed an EEG signal classification method for diagnosing epilepsy. This method is based on discrete wavelet transform and the dimension reduction is performed by PCA, independent components analysis (ICA) and LDA. The classification is carried out by SVM with a radial basis function (RBF) as a kernel. The classification rate with LDA feature extraction was the highest (100%), ICA came as second (99.5%); while the PCA reported the lowest correct classification percentage (98.75%). SVM without using PCA, ICA or LDA achieved an accuracy rate of 98%.

Wei and Hu [56] designed a human machine interface for hands-free control of a wheelchair, employing forehead EMG signal and color face image information. Five recognizable movements are deployed, namely SJC (single jaw clenching), DJC (double jaw clenching) and CJC (continuous jaw clenching) from jaw movements, and LEC (left eye close) and REC (right eye close) from eye movements. SJC and DJC patterns are recognized by using a threshold based strategy; while CJC, LEC and REC are separated through SVM with a radial-basis function kernel. An accuracy rate of over 93% in the classification was reported by SVM.

4.6. Hidden Markov Model (HMM)

HMM is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states. It has been widely used in temporal pattern recognition such as speech, handwriting, gesture and bio-signal recognition. Novák et al. [57] employed HMM in scoring of human sleep. They use three HMM states, one

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corresponding to wake state, other representing deep sleep, and the other one standing for REM sleep. Obermaier et al. [58] developed a letter spelling device operated by hand and leg motor imagery, i.e. the device is controlled through spontaneous EEG signal. They employ two HMMs to classify the EEG signal. Experimental results reported that the ability of three people in the use of the letter spelling device varied between 0.85 and 0.5 letters/min in error-free writing.

Chan and Englehart [59] used HMM to process four channels of EMG signal, in order to discriminate six classes of limb movement. Six-state fully connected HMMs are applied; each state is associated with an intended limb motion. HMM classification of continuous myoelectric signals resulted in an average accuracy of 94.63%. Solhjoo et al. [60] studied the performances of two kinds of HMMs, discrete HMM (dHMM) and multi-Gaussian HMM (mHMM), in the classification of EEG based mental task. This task implied the controlling of a feedback bar by thinking of moving left or right hand according to the cues shown to the subject. The best performance of dHMM was 77.13 % with 2 states and 16 observable symbols/state according to 0.5s segment of data; while for mHMM was 77.5% using first 0.5s segment with 8 states and 2 Gaussians/state.

4.7. K-nearest neighbor (KNN)

KNN is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). It has been widely used in statistical estimation and most recently bio-signal recognition as a non-parametric technique. Peleg et al. [61] employed KNN as a classifier of EMG signals in finger activation, in order to be used in a robotic arm. While Chaovalitwongse et al. [62] used KNN to classify normal and abnormal (epileptic) brain activities employing EEG recordings. Experimental results reported a sensitivity of 81.29% and a specificity of 72.86% in the classification on average across ten patients.

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4.8. Combination of Classifiers

Lotte et al. [63] proposed boosting, voting and stacking techniques as classifier combination strategies used in EEG signal analysis. In the Boosting technique, several classifiers are used in cascade. Each classifier focuses on the errors committed by the previous ones [64]. In voting, several classifiers are employed, each of them assigning the input feature vector to a class. The final class will be that of the majority [63]. In stacking, the outputs of the individual classifiers are used to train the "stacked" classifier. The final decision is made based on the outputs of the stacked classifier in conjunction with the outputs of individual classifiers [65].

Okamoto et al. [66] employed a hierarchical pattern classification algorithm based on boosting approach to estimate a suitable network structure. In this algorithm, the structure of the classification network is automatically constructed by adding LLGMNs (log-linearized Gaussian mixture network) as classifiers, in order to categorize EMG signal of six Japanese phonemes.

4.9. Comparison of Classifiers

Some studies [8, 32, 39, 67, 68, 69] have carried out a comparison of several classifiers with the aim of determining which classifier provides the best categorization of bio-signals. These studies evaluated the performance of each classifier in terms of statistical measures of sensitivity and specificity [39], accuracy rate [8, 32, 67] and misclassification rate [68, 69].

Huan and Palaniappan [32] used linear discriminant analysis (LDA) and multilayer perceptron neural network trained by the back-propagation algorithm (MLP-BP) to classify mental tasks using features that are extracted from EEG signal. They employ the following

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feature methods: AR coefficients computed with Burgs algorithm, AR coefficients computed with a least-squares (LS) algorithm, and adaptive auto-regressive (AAR) coefficients computed with a least mean-square (LMS) algorithm. The results showed that sixth-order AR coefficients with the LS algorithm without segmentation gave the best performances (93.10%) using MLP-BP and (97.00%) using LDA.

Omidvarnia et al. [39] compared the performances of several classifiers (Bayesian with a Gaussian kernel, Parzen estimation, K-nearest neighbor (KNN), and back-propagation neural network) in terms of statistical measures of sensitivity and specificity. They use as features: AR, power of signal in different EEG bands (α, β, δ, γ and θ), wavelet coefficients and Kalman filter. In conclusion, when AR and Kalman filter are used as features, the best classifier is KNN with accuracy rates of 93.16% and 96.13%, respectively; and when wavelet coefficients and power of signal are used as features, the best classifier is Bayesian with a Gaussian kernel with accuracy rates of 88.58% and 83%, respectively.

In the same vein, Lotte [67] compared four classifiers in order to categorize motor imagery signals using EEG signal. These classifiers are a fuzzy inference system (FIS), a support vector machines with Gaussian kernel (SVM), a multilayer perceptron (MLP), and a perceptron as a linear classifier (LC). The best performance was achieved by SVM with an accuracy percentage of 79.4 %, followed by FIS with an accuracy percentage of 79 %. MLP and LC reported accuracy percentages of 78.9 % and 76.2%, respectively. Oskoei and Hu [8] compared SVM, LDA and multilayer perceptron neural network (MLP) in classifying upper limb motions using myoelectric signals. They use four kernels (radial-basis, linear, polynomial and sigmoid) in SVM, and two multilayer perceptron neural networks, one with one hidden layer (MLP1), and the other one with two hidden layers (MLP2). The average accuracy for all kernels in SVM was approximately 95.5 ± 3.8%. The LDA was placed after SVM with the average performance of 94.5 ± 4.9%. The MLP2

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performed a similar accuracy to the SVM and LDA, while the accuracy of MLP1 dropped approximately 6%.

Zhou et al. [68] used a feature set including higher-order statistics based on the bispectrum of EEG signal for classifying left/right-hand motor imagery. Support vector machines with Gaussian kernel (SVM), linear discriminant analysis (LDA) and neural networks (NN) were used as classifiers and were compared with the winners' classifier of BCI-competition 2003, using the same BCI data set and using their own data. In the NN, they employ an input layer with 24 nodes for the features, a hidden layer with 15 nodes, an output layer with two nodes for the classes of hand motor imagery, and back-propagation algorithm to train the NN. The results showed that, using the same BCI data set and their own features, the best classifiers were NN and SVM, both with a minimal misclassification rate of 10%. However, using their own data and their own features, the best classifiers were SVM, NN and LDA, with minimal misclassification rates of 9%, 10% and 12 %, respectively.

On the other hand, Radmand et al [69] have evaluated a variety of EMG time domain feature combinations and popular classifiers. In the experiments, subjects were asked to elicit a set of contractions at a repeatable 'medium' force level of eight classes of motion (wrist flexion/extension, wrist pronation/supination, hand open, power grip, pinch grip, and a no motion) during three sessions with positional variations. The features involved in the experiments are: mean absolute value (MAV), mean absolute value slope (MAVS), wavefrom length (WL), zero crossings (ZC), slope sign changes (SSC), Willison amplitude (WAMP), variance (VAR), log-detector (LD), and 4th order auto-regression coefficients (AR). With respect to the classifiers used to distinguish the motions, these are K-nearest neighbor (KNN), support vector machines (SVM), neural network (NN), fuzzy clustering (FC), linear discriminant analysis (LDA), and Mahalonobis distance (MD). The results

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showed that adding Willison amplitude (WAMP) feature to the commonly used time domain feature set combined with LDA classifier reduces the averaged absolute classification error by 1.4%.

In the same context of classification of EMG signal, Scheme and Englehart [70] have reviewed the state-of-the-art of EMG pattern recognition for control of upper limb prostheses. In this study, they mention as the most popular choices of classifiers the following ones: linear discriminant analysis, support vector machines, and hidden Markov models. They explain that the main advantage of linear discriminant analysis is its simplicity of implementation and ease of training.

5. Controller

In the controller stage, output commands produced in the classification stage are fed to a robot or an assistive device such as wheelchairs, robotic arms or computers. In the following sections, a number of EMG and EEG control applications are outlined.

5.1. EMG non-invasive applications

Sörnmo and Laguna [5], and Oskoei and Hu [2] have shown that some EMG non-invasive applications are:

1) kinesiology, since EMG can assist on the study of motor control strategies, mechanics of muscle contraction and gait;
2) ergonomics, as EMG provides a valuable, quantitative measure of muscle load, often used to asses physical load during work, therefore it can help to avoid work-related disorders and design better workplaces;
3) prosthesis control, inasmuch as the control signal is derived with surface electrodes placed over muscles or muscle groups under voluntary control within the residual limb [8, 22, 43, 61];

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4) wheelchair controllers [52, 56, 71];

5) virtual keyboards [72]; and

6) diagnoses and clinical applications, such as functional neuromuscular stimulation [54] and detection of preterm births based on uterine myoelectric signals.

More details can be seen in table 4.

Table 4

EMG applications

	Feature extraction	Classifier	Application
Multifunction prosthesis			
1999, Huang and Chen [22]	IEMG, VAR, bias ZC, SSC, WL, WAMP and AR	BPNN	A myoelectric discrimination system for a multi-degree prosthetic hand
2002, Peleg et al. [61]	AR and discrete Fourier transform	KNN	Finger activation for using a robotic prosthetic arm
2006, Chu et al. [43]	Wavelet packet transform	Multilayer perceptron	Control of a multifunction myoelectric hand
2008, Oskoei and Hu [8]	MAV, RMS, WL, VAR,ZC, SSC, WAMP, MAV1, MAV2, power spectrum, AR, FMN and FMD	SVM	Classification of upper limb motions using myoelectric signals
Wheelchairs			
2008, Firoozabadi et al. [52]	MAV	SVM	Hands-free control system for operating a virtual wheelchair
2010, Tamura et al. [71]	Not indicated	Threshold algorithm	Hands-free control system for electric wheelchairs with facial muscles
2010, Wei and Hu [56]	MAV, RMS, WL, ZC, FMN and FMD	SVM	Hands-free control of electric wheelchair with forehead EMG signals and color face images
Other applications			
2004, Jeong et al. [72]	IEMG, difference absolute mean value	Fuzzy min-max NN	Using a computer by clenching teeth
2010, Gurmanik et al. [54]	AR	SVM	Differentiating neuromuscular disorders

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5.2. EEG non-invasive applications

Many EEG non-invasive applications have been reported [4, 5, 73], including the following ones:

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1) Diagnosing mental disorders including epilepsy and schizophrenia [33, 55], also sleep disorders, such as insomnia, hypersomnia, circadian rhythm disorders and parasomnia;
2) Monitoring mental tasks [32, 34]; and
3) Controlling spelling program, computer cursor for communication with the external world, video games, intelligent wheelchair [51, 74, 75], television, robotic arm or a neuroprosthesis that enables the multidimensional movements of a paralyzed limb.

More detailed summary is given in table 5.

Table 5

EEG applications

	Feature extraction	Classifier	Application
Mental tasks			
2002, Yom-Tov and Inbar [34]	AR, PSD, Barlow, mean amplitude difference and standard deviation of the amplitude difference between every pair of recorded electrodes	Combination of a genetic algorithm and SVM	Classification of movement-related potentials recorded from the scalp
2004, Huan & Palaniappan[32]	AR	BPNN and LDA	Two-state BCI from EEG signals extracted during mental tasks
Wheelchairs			
2005, Tanaka et al. [74]	Coefficient of correlation	Recursive training (Euclidean distance)	Electroencephalogram-based control of electric wheelchair
2007, Leeb et al. [75]	Logarithmic band power	Threshold algorithm	BCI control of a wheelchair in virtual environments
2008, Choi et al. [51]	Common spatial pattern	SVM	Control of a wheelchair by motor imagery in real time
Mental and neurological disorders			
2007, Sabeti et al. [33]	AR, band power, fractal dimension and wavelet energy	LDA and SVM	Selecting relevant features for EEG classification of patients
2010, Subasi and Gursoy [55]	Mean of absolute values, standard deviation of the coefficients, average power of wavelet coefficients in each sub-band, ratio of absolute mean values of adjacent sub-bands	SVM	Diagnostic decision support tool for physicians treating potential epilepsy

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6. Challenge issues in EMG and EEG control systems

One of the most significant current discussions in the area of EMG prostheses is about the existing gap between the industry and the academic achievements regarding

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myoelectric control of artificial limbs. Jiang et al. [76], have explained the main reasons contributing to this. First, despite the academic community has presented sophisticated techniques for classifying EMG signals, (e.g., fuzzy logic, neural networks, mixing of classifiers), these techniques do not offer simultaneous and proportional control of the prostheses. On the other hand, the majority of commercial prostheses employ the simplest classification method, i.e., a threshold that is compared with the EMG signal to trigger functions, leading to offer limited and simple functions. Second, most of the myoelectric control systems proposed by the academic community may not be adaptive to the changes of the EMG signal characteristics presented in a real scenario due to their development under controlled laboratory conditions. Third, the functional movements of a limb involved for achieving a task are generally complex; therefore there is the need of combining different sensor modalities to improve the control of prostheses rather than using merely EMG.

Some studies have proposed methods to provide simultaneous and proportional myoelectric control. For instance, Muceli and Farina [77] have used artificial neural networks to estimate kinematics of the complex wrist/hand from high-density surface EMG signals of the contralateral limb during mirrored bilateral movements in free space. The neural networks are trained with the Levenberg–Marquardt back-propagation algorithm. In the same vein, Hahne et al. [78] compared control accuracies of linear and nonlinear regression methods (linear regression, mixture of linear experts, multilayer-perceptron, and kernel-ridge regression) for independent, simultaneous and proportional myoelectric control of wrist movements with two degrees of freedom (DOFs). EMG signals from ten healthy subjects and one person with congenital upper limb deficiency were obtained to assess the accuracies of these methods in terms of the number of electrodes and the amount and diversity of training data used. They identified that a logarithmic

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transformation of the established variance feature linearized the relationship between EMG and wrist angles. This allows applying very simple and computationally cheap linear methods. In [79], four DOFs of a physical hand can be controlled simultaneously and independently by processing peripheral neural correlates in real time. This is achieved by using EMG signal from intramuscular electrodes on the extrinsic flexor muscles of subjects.

Furthermore, it is becoming increasingly difficult to ignore the impact of external factors on the act of wearing prosthesis and using it in a functional manner. According to Scheme and Englehart [70], some of these external factors are: electrode shift, variation in force, variation in position of the limb, and transient changes in EMG. In this context, Fougner et al. [80] propose two possible solutions to reduce the adverse limb position effect: (1) collection of EMG signal and training of the classifier in multiple limb positions, and (2) measurement of the limb position with accelerometers. They conducted experiments with ten normally limbed subjects, and their results showed a reduction in the average classification error from 18% to 5.7% by using the first method and 5.0% by using the second method. Based on these results, they conclude that sensor fusion (using EMG and accelerometers) may be an efficient method to mitigate the effect of limb position. Similarly, Cipriani et al. [81] showed that variations in the weight of the prosthesis and upper arm movements significantly influence the robustness of a traditional classifier based on a KNN algorithm, causing a significant drop in performance. They suggest adding inertial transducers (e.g. multi-axes position and acceleration sensors) to the EMG signal classifier in order to recognize the effects of the weight and inertia of the prosthesis.

In the case of EEG control systems, Milán et al. [82] and Nicolas-Alonso and Gomez-Gil [83] present the following challenges issues that need to be addressed. First, users require expert assistance to interact with a system controlled exclusively via EEG signals; hence

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an approach called hybrid Brain Computer Interface has been proposed to cope with this issue, i.e., the use of EEG signal in conjunction with other signals (e.g., EMG signal). Second, the performances of EEG control systems are affected by noisy and low-bit-rate outputs. Shared autonomy techniques could tackle this challenge by analyzing information about the environment to obtain a better user's intent (e.g., obstacles perceived by the sensors in the control of a wheelchair via EEG signal). Third, the portability and ease of use of an EEG control system are compromised by the majority of current EEG technology, mainly because the EEG signal is collected through a conventional electrode cap, which is connected to the computer via wires and their electrodes need to be moistened. Different companies (Emotiv, Quasar USA, NeuroSky) have developed wireless prototypes based on dry electrodes to overcome this issue. Finally, most EEG control systems remain at the research stage without being used in the daily life of people.

7. Conclusions

This document provides an overview of how bio-control systems are designed, in particular on EEG and EMG control systems. As explained, the design of bio-control systems has four stages: data acquisition & segmentation, feature extraction, classification and control. Furthermore, techniques used in each stage were described, as well as some applications of the control systems.

This paper has also shown that despite the technology is extremely useful for improving the quality of life of disabled and elderly people, there are several challenge issues referring to the implementation of EMG and EEG control systems that need to be solved, e.g., i) although the academic community has proposed sophisticated techniques for classifying EMG and EEG signals, the commercial applications accomplish simple tasks due to the use of basic classifiers; and ii) most of the EMG and EEG control systems proposed by the academic community may not be adaptive to the changes of the signal

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characteristics presented in a real scenario due to their development under controlled laboratory conditions.

It is clear that bio-control technologies will begin to converge to address the key issues described earlier, and consequently improve our human-machine interaction. In the near future we will see highly robust and flexible bio-control systems, which are based on various bio-signals such as voice, muscle contractions, brain waves and gestures. These control systems will become increasingly simple and intuitive, and no training will be required, namely plug and play. These bio-control systems will have ability to understand human intentions and emotions, and adapt the dynamic changes in the real-world. It is no doubt that these big inventions will change our life style forever in the 21st century just as the computers did in the 20th century.

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