A survey on bio-signal analysis for human-robot interaction

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ABSTRACT

The use of bio-signals analysis in human-robot interaction is rapidly increasing. There is an urgent demand for it in various applications, including health care, rehabilitation, research, technology, and manufacturing. Despite several state-of-the-art bio-signals analyses in human-robot interaction (HRI) research, it is unclear which one is the best. In this paper, the following topics will be discussed: robotic systems should be given priority in the rehabilitation and aid of amputees and disabled people; second, domains of feature extraction approaches now in use, which are divided into three main sections (time, frequency, and time-frequency). The various domains will be discussed, then a discussion of each domain's benefits and drawbacks, and finally, a recommendation for a new strategy for robotic systems.

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1. INTRODUCTION

Human-robot interaction (HRI) is a rapidly expanding field of study and application. There are numerous complex problems in this field, and solutions that have a positive societal impact are possible. due to their interdisciplinary nature, researchers in the discipline must understand their studies from a larger perspective [1]. HRI is an interdisciplinary topic that encompasses essential research in domains such as human-robot interaction (HCI), artificial intelligence (AI), control systems, pattern recognition, psychology, electronics, mechanics, social communication, behavioral expression systems, and neuroscience, among others. Most HRI experiments involve the development of a robot that interacts with the environment or a specific item. They devised a movement strategy for a particular situation (based on physical attributes) without considering the impulse or stream of thinking that characterizes human activity [2].

To develop the robotics hardware and software needed to create a successful human-robot interface. A range of fields must collaborate, analyze human behavior when interacting with robots in various social circumstances, and design the aesthetics of the robot's embodiment and behavior and the domain knowledge required for specific applications. Due to the numerous disciplinary jargon and processes [3]. Monitoring and evaluating the patient's physiological data is crucial in physical therapy to assess treatment effects and regulate assistive devices during the rehabilitation process. These two forms of data are detected using various sensors, including electromechanical sensors (such as accelerometers) [4]. And biosensors (such as electromyography (EMG) [5], as well as force sensors [6], Electroencephalography (EEG), and magnetoencephalography (MEG) have been used. Electromechanical sensors can effectively detect biological data [5], [7].

The number of possible bio-signals is enormous, given that there are many physiological systems of relevance. Bio-signals include everything from a visual evaluation of the patient to bodily indicators captured by sensors in a larger sense [8]. Machine learning (ML) offers powerful algorithms for perception and knowledge that may be used to create solid and versatile high-level recognition systems. Image processing techniques and entropy distance, wearable cameras, and inertial sensors were used to recognize human actions and detect falls. A 99% adaptable system based on decision trees and four sensors coupled to the body system was constructed to identify daily behaviors such as standing, sitting, and walking [9].

This research paper is divided into the following sections: the second section explains how existing studies' research was gathered. In the next area, we will go over how to evaluate human-robot interactions. Following that, the model for gesture recognition techniques is presented. The last section compares domains for feature extraction in pattern recognition techniques. The study's conclusion was then discussed.

2. RESEARCH METHOD

Unlike previous surveys, this work provides a thorough review of current advancements in prosthesis control based on upper-limb myoelectric control in terms of model robustness, adaptation, and reliability. Efforts will be made in three areas in this context: i) primary consideration should be given to robotic systems in the rehabilitation and assistance of amputees and disabled persons; ii) domains of features extraction techniques now in use, categorized into three types (time, frequency, and time-frequency); and iii) a review of the benefits and drawbacks of each domain that has been evaluated. Elsevier, PubMed, IEEE, SpringerLink, Google Scholar, and Wiley Online Library were used to conduct literature searches for this review. Search terms included surface EMG (sEMG), myoelectric control, bio-signals analysis, rehabilitations, assistances, classification, regression, features extraction, features domains, robustness, reliability, domain adaptability, multi-modal, sensor fusion, confidence estimate, uncertainty analysis, and so on. Publications from 2010 to 2021 were favored, while the time period was extended in some situations. After doing a literature search, we carefully examine each article to exclude those that do not meet the following criteria: i) the literature must focus on upper-limb motion estimates utilizing machine learning control and ii) technical contributions should be relevant to one of the three targets, namely robotic systems in the rehabilitation and assistance of amputees and disabled people, feature extraction, and their benefits and drawbacks. For these objectives, we first chose 74 linked papers.

3. HUMAN-ROBOT INTERACTION BASED ON BIOMEDICAL SIGNALS

Bio-signals are the critical source of information on biosystem functioning and provide communication between them. It is, as all signals require the transmission of energy. Bio-signals can be evaluated directly from their biological source; however, external power is frequently used to study physiological and external power interactions. A transducer converts a bio-signal into an electric signal that can be measured. In most cases, the analog signal is converted to a digital (discrete-time) signal [10].

3.1. Electroencephalography signal

The EEG is a technique for detecting electrical activity in the brain. Because of its exceptional temporal sensitivity, EEG is primarily used to detect changes in brain activity. EEG testing may benefit patients with seizures, epilepsy, or unusual spells. This comes with several benefits. EEG signals are linked to mental functions in the brain, making them less susceptible to an amputation. Second, muscle strain has little effect on EEG-based movement estimations. As a result, using EEG in conjunction with another bio-signal, such as sEMG, has piqued researchers' curiosity [11]–[13], where the features of two signals can be analyzed sequentially or concurrently.

In study [14], researchers created a new EEG dataset that was infected with real-time motion artifacts and discovered that coherence was a better similarity metric between the motion artifact-infected EEG and motion sensor data. This real dataset was created to aid researchers working on EEG motion artifact reduction techniques by allowing them to compare and contrast existing methods as well as develop new models. Hadiyoso *et al.* [15] presented a study comparing the coherence of EEG signals in mild cognitive impairment (MCI) patients and healthy people. Its goal is to make each group's feature visible so that the coherence value can be used to detect early Alzheimer's disease via EEG analysis. It looked at the inter-and intra-hemispheric coherence of the electrode pairs. MCI sufferers' mean coherence was lower than healthy people were. In this experiment [16], the Wavelet technique to evaluate the EEG signal successfully classified a person's brain dominance. This is due to the Wavelet's ability to assess brain signals based on scale and direction. The benefits of EEG signals include being less reliant on amputation conditions. On the other hand, the disadvantages include a low signal-to-noise ratio (SNR), a slow data transfer rate, poor estimation accuracy, and restricted user adaptability.

3.2. Electromyogram signal

The EMG signal, which is frequently employed in psychophysiology to study the relationship between cognitive expression and physiological responsiveness, measures and records the electrical potential generated by muscle cells [17]. The two categories of EMG sensors are sEMG and intra muscular (iEMG). Muscle cells produce EMG signals, which are bioelectric signals used in a variety of applications including sports science, ergonomics, assistive technology, and rehabilitation [18].

The method for classifying various hand gestures that have been developed will be helpful in human-computer interaction as well as in controlling devices such as prostheses, virtual objects, and wheelchairs; for example, In [19], researchers used time-domain EMG features that were normalized to the area under the averaged root mean square curve to improve gesture recognition accuracy (AUC-RMS). From each channel's active EMG signals, the four basic time-domain features were extracted: mean absolute value (MAV), zero crossing, waveform length (WL), and slope sign change (SSC). The researchers used five machine-learning algorithms to classify the three different hand motions: k-nearest neighbor (k-NN), discriminant analysis (DA), naive Bayes (NB), random forest (RF), and support vector machine (SVM). The results showed that both normalizing approaches improved performance indicators such as accuracy, F1 score, Matthew correlation coefficient, and Kappa score compared to the original EMG features.

EMG signal is employed as a signal for intention prediction of human motion in numerous robotic applications, particularly in human-robot interaction systems. Most significantly, it is used to calculate the kinematics of upper limb movements, which are the most active sections of the human body and are necessary for daily tasks [20]. Patricia *et al.* [21] looked at four adaptive learning algorithms, two of which had previously been evaluated in the prosthetic field, to see if they could help amputees learn to use an sEMG-based prosthetic hand in less time. By increasing the number of source subjects available, they compared their performance when dealing with different types and numbers of hand movements. As a result, they demonstrated that adaptive learning has much potential in this field.

Researchers investigate several mother wavelet functions in discrete wavelet transforms (DWT), and continuous wavelet transforms (CWT) in [22]. The performance of several mother wavelets in DWT and CWT is also investigated at various decomposition levels and scales. Each CWT and reconstructed DWT wavelet coefficient has extracted its MAV and WL features. The SVM, a popular machine learning technique, recognizes different hand movements. As a result, DWT outperforms CWT in rehabilitation and clinical application.

3.3. Mechanomyography signal

Acoustic myography (AMG) is the term for when microphones pick up an MMG signal [23]. During contraction, they measure the mechanical responses of muscle fibers' lateral oscillation at low frequencies (2–200 Hz). Unlike sEMG, MMG is unaffected by changes in skin impedance or sensor positioning sensitivity [24]. MMG can be created using a variety of transducers, including piezoelectric touch sensors and accelerometers [25]. As a result, combining these two signals has piqued people's interest. In [26], researchers proposed a hybrid EMG and MMG acquiring method for hand motion detection and discovered that combining EMG and MMG features reduced classification error. On the other hand, Zhang e*t al.* [27] developed a structure-level strategy for post-processing sEMG-based hand gesture detection and feature-based fusion techniques using MMG signals as movement onset/offset detectors.

4. HUMAN-ROBOT INTERACTION PERFORMANCE EVALUATION METHODS

Many studies have been carried out to document user experiences and the psychological impacts of human-computer interaction. Using features of psycho-physiological data collected in real-time, they deduced the subject's biology. There are varieties of research findings for various study issues along these lines. Still, very little of the accumulated data can formulate speculative hypotheses or establish more detailed research questions [28].

Multiple events, such as subject moves, electrode disconnection, fluctuating temperatures, humidity levels, subject-dependent physiological abnormalities, electrostatic artifacts, and other unrelated user actions, may occur during the data collection operation, causing the sensor signal to degrade and external interference [29]. As a result, signal-preprocessing approaches need to be applied to the unprocessed signal, typically the initial stage in developing an ML system. It requires synchronizing the signals from various sensors, removing data loss and null values, and perhaps other tasks: filtering, noise removal, and outlier elimination (usually by linear interpolation). The type of sensor utilized and the goal of the study state the filter type and characteristics, which are as [30]: HRI's principal purpose is to equip robots with various skills to interact with people more effectively. However, as more people contact robots daily, it is becoming increasingly necessary for untrained users to engage with and use these robots efficiently. A robot hand a wheelchair [31], or a humanoid robot [32] are examples of external mechanical equipment that have grown increasingly common in brain robot interaction (BRI) [33]–[35].

4.1. Rehabilitation and assistance by using human-robot interaction

Rehabilitation robots are one area of study that focuses on using robotic systems to augment and analyze rehabilitation processes. These devices have been created to assist with various therapeutic preparation and sensory function testing methods [36]. For example, robotic rehabilitation is a valuable tool for treating motor control in people who have had a stroke or another type of motor impairment [37]. Alternatively, assistive robotics strives to help people with impairments execute their daily life activities (DLAs) with greater freedom. Moving, gripping, as well as handling objects, and eating, are examples. Consequently, robotic devices are used daily for therapy and assistance. A growing number of research efforts have recently focused on assistive and rehabilitative robots due to rapidly growing technical breakthroughs in machine learning, sensors, data processing, computation, prototype testing, and production, as well as massive social demands such as mobility aids for older people [38], [39] are a couple of examples.

4.1.1. Assistive robotics

Millions of people worldwide have upper or lower limb limitations, limiting their reach and ability to control objects. Geriatric patients, older patients, patients with muscular dystrophy (MD), amyotrophic lateral sclerosis (ALS), Multiple sclerosis (MS), cerebral palsy (CP), spinal muscular atrophy (SMA), as well as others who have severe motor paralysis, are among the patients [40]. This emphasizes a need for a low-cost, moderate assistive device that enables patients to grasp objects, interact safely with their environment, and gain independence. Researchers have developed assistive robotic manipulators (ARMs) in wheelchair-mounted and fixed desktop forms [41]. Many studies have focused on building novel user interfaces to improve the performance of helpful robotic manipulators. Furthermore, as more embedded system computers become available, artificial intelligence is increasingly used to aid patients in executing activities more autonomously and successfully. A sensitive joystick, similar to intelligent wheelchairs, is the most often used user interface for assistive robotic manipulators [42].

4.1.2. Robotic prostheses

The use of a robotic prosthesis effective Prosthesis, also known as a rehabilitation robot, is a type of rehabilitation robot attached to a patient's body and performs the duties of the missing limb during daily activities. Patients frequently order and regulate their function via muscle or brain impulses in real-time. The human body interacts directly with the robotic prosthesis. As a result, designing robotic prostheses, physical qualities, humanoids' looks, knowledge of user intent, reproducing movements, grasp patterns of the complete human body, or force effort are essential factors to consider [43]. Many recent research efforts have focused on producing prosthetics that resemble a biological limb's capabilities. The key to successful improvement is acquiring a comprehensive technique for comprehending the patient's desire to perform a task and detecting the environment [44]. The mobility and dynamic control system of the robot may gather numerous bio-signals in order to create a recognition algorithm and achieve the user's goal [45]. Prosthetic operating methods, which significantly impact the device's comfort, define how muscle activation data collected by sensing modalities are used to handle the prosthesis [46].

Upper limb prosthetics are frequently controlled using pattern-recognition-based proportional control approaches and combinations. On chosen degree of freedom (DOF) shafts for the Prosthesis, balanced control technology also offers a position, velocity, or force control, with a motion property adjusted proportionally to the intensity of muscle contractions [47]. Although direct scaling control of prosthetic fingers is more natural than grip selecting, the user may find it more challenging it to modify the position of the fingers for the work because there are usually only a few control sites available [48]. Deep learning (DL) has only recently been used in sEMG research, even though pattern recognition approaches have been used for decades. Because of the introduction of large sEMG data sets and the development of evolutionary algorithms, DL had already shown significant potential in the sEMG pattern identification of an artificial hand. sEMG and DL are employed in various foundational gesture recognition investigations [18].

5. PATTERN RECOGNITION SYSTEM

Although the concept of gesture recognition techniques is similar, each step has its own style; also, not all study uses all phases of the standard framework. As a result, we recommend a six-step conventional strategy: data collection, data preparation, feature extraction, classification algorithms, post-processing, and performance evaluation. Figure 1 shows how to identify sEMG signal patterns using conventional ML-based methodologies.

5.1. Data acquisition

Two or more electrodes were put in the front and rear of the lower arm to acquire the EMG signal, believing that the cross-talk content for each signal would be essentially the same for each movement. The purpose would have been to characterize the signal's varied patterns for different directions [49]. Because there are only a few coupled sensors over the muscles in this setup, most gesture labels are assigned to sEMG [50].

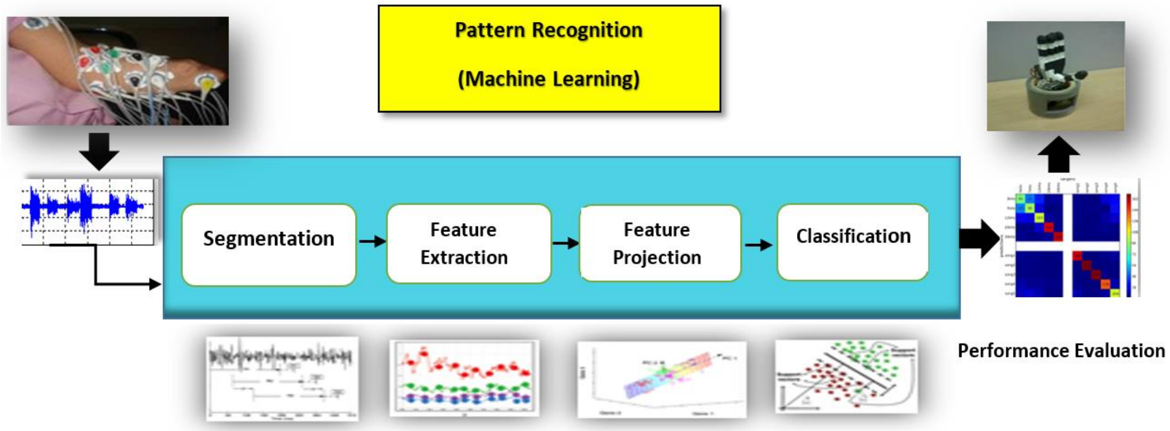

Figure 1. The general framework for describing the interactions between the user and the robotic prosthesis

5.2. Data preprocessing

A single-channel EMG signal is segmented for post-processing and production of muscle activation patterns. Each muscle is independently recorded since not all EMG recording channels are sufficient to account for movement cycles. The applicability of particular EMG channels is determined by the mode of muscle activity and the number of onsets and cessations during each movement cycle. For example, muscles in a phasic manner with only one activity interval within the movement cycle produce the most appropriate EMG signals [51]. Because of the limited EMG voltage amplitude and poor EMG signal in stroke patients, recognizing motion intent based on EMG presents an additional challenge due to the reduced SNR; hence, standard signal processing may not effectively extract the user's purpose. Emerging machine-learning signal processing algorithms may increase EMG signal processing quality while eliminating the need for onsite manual calibration and threshold setup operations, resulting in a user-friendly solution [52]. To determine EMG-based hand movement intent, neural network-based machine learning techniques such as a convolutional neural network (CNN) were used, demonstrating the ability to overcome these challenges in EMG signal feature extraction and system calibration [22].

5.3. Feature extraction

Extracting features from a signal to achieve consistent categorization is known as feature extraction. The most important step in biomedical signal classification is feature extraction because if the features are not extracted correctly, the classification performance will suffer. The feature extraction stage should reduce the original data to a smaller dimension while retaining most of the useful information from the initial vector. As a result, it is critical to identify the fundamental elements that define the collection based on its nature. Because they are the most typical values for determining the distribution of biological signals, different statistical features can be retrieved from each subsample data point. Biological signals' min, max, mean, median, mode, std, variance (VAR), 1st, 3rd, and inter-quartile range (IQR) can be used as features [53]. ML employs feature engineering to achieve this goal, time domain (TD) features, time-serial domain (TSD) features, frequency domain features, and time-scale or time-frequency domain characteristics are all included [54].

5.3.1. Time-domain features

The TD values are determined by the raw sEMG, which are time functions. They are commonly used because they have a lower processing complexity than other sEMG features. MAV, root mean square (RMS), integrated EMG (iEMG), histogram (HIST), zero crossings (ZC), standard deviation (SD), SSC, waveform length (WL), Willison amplitude (WAMP), variance (VAR). Other time-domain components are frequently used, commonly used together [18]. Table 1 presents a brief use of Time-domain features. Hamedi *et al.* [55] Use the integrated (INT), MAV, mean absolute value slop (MAVS), RMS, VAR, and WL time-domain feature extraction methods on signals. To obtain recognition accuracy and assess the efficacy of each feature extraction method, the features are categorized using Fuzzy C-means.

Table 1. Shows the domain-specific features

Category	Feature	Formula	Time-domain
Time domain	MAV	$MAV = \frac{1}{N}\sum_{i=1}^{N}\lvert xi\rvert$	Indication of muscle contraction levels
	RMS	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} xi^2}$	A Gaussian random process with amplitude modulation.
	iEMG	$\text{iEMG} = \sum_{i=1}^{n}\lvert xi\rvert$	An index for detecting the onset of a condition
	ZC	$ZC = \sum_{i=1}^{n-1}[sgn(xi \times xi+1) \cap \lvert xi - xi + 1\rvert \geq threshold]$ $sgn(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & otherwise \end{cases}$	A feature that makes an approximation of frequency domain properties.
	SSC	$SSC = \sum_{i=2}^{n-1}[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]]$ $f(x) = \begin{cases} 1, & if\ x \geq threshod \\ 0, & otherwise \end{cases}$	A method for representing the signal's frequency information.
	WL	$WL = log(\frac{\sum_{i=0}^{n-1}\lvert \Delta x\rvert}{\sum_{i=0}^{n-1}\lvert \Delta 2x\rvert})$	The signal's frequency, duration, and amplitude are all detailed.
	WAMP	$f(\Delta i) = \begin{cases} 1, & if\ \Delta i \geq threshod \\ 0, & otherwise \end{cases}$ $\Delta i = \lvert xi + 1 - xi\rvert$	Indicator of muscle contraction intensity.
	VAR	$VAR = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2$	The sEMG signal's power index
	V-order (V)	$V = \left(\frac{1}{N}\sum_{i=1}^{N} x_i^v\right)^{\frac{1}{v}}$	A nonlinear detector for estimating the force of muscle contractions implicitly.
	simple square integral (SSI)	$SSC = \sum_{i=2}^{n-1}[f[(x_i - x_{i-1}) \times (x_i - x_{i+1})]]$ $f(x) = \begin{cases} 1, & if\ x \geq threshod \\ 0, & otherwise \end{cases}$	The sEMG signal's energy index
Frequency domain	total power (TP)	$TP = \sum_{j}^{M} pi$	The sEMG power spectrum as a whole.
	modified phase (MP)	$MP = \frac{1}{M}\sum_{j=1}^{M} pi$	The EMG power spectrum's average power
	mean frequency (MNF)	$MNF = \frac{\sum_{j=1}^{M} fjPi}{\sum_{j=1}^{M} Pi}$	Frequency average
	median frequency (MDF)	$\sum_{j=1}^{MDF} pj = \sum_{j=MDF}^{N} pj = \frac{1}{2}\sum_{j=1}^{M} Pj$	A frequency splits the sEMG power spectrum into two regions of equal amplitude.

Notes: *N* denotes the number of sampling points; *xi* denotes the sEMG signal of the *ith* sampling point; *M* denotes the total number of frequency bins; *PJ* denotes the sEMG power spectrum, and *fj* indicates the frequency of the range of the *jth* frequency bin.

According to Balbinot and Favieiro [56], the system was created with a small number of myoelectric signal acquisition channels (up to eight) and a more robust artificial intelligence technique in mind. By describing seven different motions, he was able to demonstrate the system's validity. They used an eight-input neuro-fuzzy network with one output to calculate the RMS value for each of the eight channels. The average accuracy for seven different moves was 86 %. On the other hand, Wu *et al.* [57] study the use of a single-channel signal characteristic of a single-channel time-domain sEMG envelope in a gesture detection system. The modified KNN algorithm and the soft margin SVM method are used to classify five different types of motions. Using the improved KNN algorithm and the smooth margin SVM approach, they were able to attain gesture recognition scores of 75.8% and 79.4%, respectively. Table 2 provides more information.

5.3.2. Frequency domain features

The FD features are calculated using the Fourier transform of the sEMG signal's autocorrelation function, which is then estimated using a period gram or parameter method. Other frequency domain properties of sEMG signals include frequency ratio (FR), TP, MP, MDF, MNF, power spectrum (PS), and others [58]. The detailed information is shown in Table 1. Awang *et al.* [59] create an integrated method for identifying brain changes during rest and writing situations using power spectral density (PSD) estimation for selected representative EEG data. The k-NN classifier is used, which has an average accuracy of 95% researcher in [60] used the short-time Fourier transform on raw EEG data to determine the power distribution for each frequency band. The stationary wavelet transform was used to remove artifacts, and k-NN and SVM were used to classify them.

The power distribution for each frequency band was determined using the short-time Fourier transform on raw EEG data. Artifacts were removed using the stationary wavelet transform, and they were classified using k-NN and SVM. They show that k-NN has the best results for frequency bands between 4 and 50 HZ, with an average accuracy of 94.208% and 90.816% using SVM.

Djemal *et al.* [61] proposed a system for extracting features. Using event-related de-synchronization and synchronization strategies, the classification accuracy of three-class motor imagery (MI) brain to computer interaction (BCI) is improved. The classification method uses fast Fourier transforms (FFT) and autoregressive (AR) modeling to combine phase and amplitude aspects of brain signals. For two BCI competition datasets, 86.06 % and 93% classification accuracy were achieved using sequential forward floating selection (SFFS) and multi-class linear discriminant analysis (LDA) classifiers. Acharya *et al.* [62] developed a computer-aided diagnostic (CAD) technique that can classify the three classes of EEG segments with 99.7% classification accuracy by using a fuzzy Sugeno classifier and non-linear features based on higher-order spectra (HOS), fractal dimension, and Hurst Exponent. Table 3 provides further information time-dependent power spectrum descriptors (TD-PSD) [63] and temporal-spatial descriptors (TSD) [64] are two new features that have recently been proposed to increase the robustness of feature extraction. Because a single feature, such as Phinyomark's feature set, may only supply so much information, combining elements from multiple groups is a smart concept [65].

Table 2. Summary of previous literature utilizing time domain features extraction

Ref	Year	Signal type	Features	Classification	Accuracy
[55]	2012	sEMG	INT, MAV, MAVS, RMS, VAR, and WL	Fuzzy C-means (FCM)	90.8%
[56]	2013	sEMG	RMS	neuro-fuzzy	86%
[57]	2018	sEMG	IEMG, MAV, VAR, Standard deviation, Average energy, MAX, SSC, Skewness, Kurtosis	KNN+SVM	75.8-79.4%
[66]	2021	EMG, ECG, hand and foot galvanic skin response (hand GSR) and (foot GSR)	statistical features	SVM	88.89%

*Galvanic skin response (GSR)

Table 3. Summary of previous literature utilizing frequency domain features extraction

Ref	Year	Signal type	Features	Classification	Accuracy
[59]	2012	EEG	Spectral density of power (PSD)	k-NN	95%
[62]	2012	EEG	Higher-order spectra higher-ordertal dimension and hurst exponent-based nonlinear features	Fuzzy Sugeno Classifier	99.7%
[61]	2016	EEG	FFT + auto regressive (AR)	LDA	86.06%-93%
[60]	2020	EEG	Short-time fourier transform	k-NN+SVM	94.20%-90.81%

5.3.3. Time-frequency domain features

The energy of the sEMG signal in time and frequency is calculated using time–frequency domain (TFD) features, which is a typical feature extraction approach. The frequency bands are formed by different wavelet coefficients, and statistical indicators are extracted as TFD features. When the basic wavelet function db4 is utilized as the wavelet transform equation, the raw sEMG signal is partitioned into three levels.

$$WT = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t)\psi^* \left(\frac{t-\tau}{a}\right) dt \tag{1}$$

Where, a is the scale parameter, the mother wavelet is ψ (t), and the translation parameter is τ. The *ith* level decomposition coefficient *ci* (*ci*=one of [cD1, cD2, cD3, cA3]) has a length of *ni.*; μ is the average of *ci* [57].

5.3.4. Parameter model

The parameter model's central premise is that raw sEMG data sequence information should be treated as a time series. So, the sEMG signal is stable on short notice. The coefficients and intercept of the fourth autoregressive model are often used as characteristic values [67].

5.3.5. Performance feature extraction domains

By thoroughly reading various publications, including primary methodologies for one-dimensional signal linear analysis in the time, frequency, or time-frequency domain. Several common interest approaches were examined and rated for their overall benefits and drawbacks. The advantages and disadvantages of several feature extraction algorithms for gesture detection are shown in Table 4.

Table 4. Feature extraction approaches (pros and cons) [54], [68]–[70]

Domain name	Pros	Cons
Time	– TD characteristics are derived directly from raw signal time series without any manipulations. – Implementation is simple. – The computational load must be kept to a minimum.	– Because they are entirely made of time, Time-domain windows are adaptable. – Depending on the values of the R-R interval,
Frequency	– This is a valuable tool for signal processing in a stationary environment – It is better for narrowband signals like sine waves. – It outperforms virtually all other approaches available in real-time applications	– Non-stationary data analysis, such as EEG suffers from a flaw. – Because of its poor spectrum estimation, it cannot be used to analyze short EEG signals. – Its spectrum estimation is poor, so it cannot be used to analyze short EEG signals.
Time-Frequency	– It has a variable window size, with a large one at low frequencies and a small one at higher frequencies. – It excels at analyzing transient and fast signal changes. – Better at analyzing erratic data patterns, such as impulses that occur at irregular intervals.	– It is necessary to choose a suitable mother wavelet.
Parameter model	– The use of augmented reality (AR) techniques reduces spectral loss and improves frequency resolution – Excellent frequency resolution is provided. – Spectral analysis based on the AR model is helpful when analyzing small data segments.	– It is difficult to choose the model order in AR spectral estimation. – The AR technique produces poor spectral estimation when the estimated model is not appropriate, and the model's orders are incorrectly specified. – Solid biases and even large variability can easily influence it.

5.4. Pattern classification

The final stage of pattern recognition for EMG control of the prosthesis is pattern classification. Following that, a specific tool can be chosen based on the system's requirements and characteristics. One of the most widely used pattern detection methods in myoelectric signals is support vector machines (SVM), which discover an n-dimensional hyperplane that can divide a set of extracted input features into different classes [71].

This approach outperforms other classifiers in recognizing complicated patterns, such as artificial neural networks (ANN) and linear discriminant analysis (LDA). On a number of occasions. The SVM is based on the following basic concepts: i) hyperplane divider, ii) kernel function, iii) optimal separation hyperplane, and iv) soft margins (tolerance of hyperplane). SVMs have a high classification accuracy because they may be coupled with other classification methods to achieve diverse classification goals. They also have a high rate of accuracy [72].

5.5. Performance evaluation

5.5.1. The metrics used for models' evaluation

Prediction accuracy is usually one of the most important criteria for evaluating the functionality of a pattern recognition model. Offline testing evaluates the model's performance using accuracy, recall, precision, standard deviation, and other metrics. Error measures such as mean square error (MSE), root mean square error (RMSE), normalized root mean square error (NRMSE), and correlation coefficient are commonly used to classify these observations [73].

Furthermore, the data in the model's test set for each category and generation must be balanced; otherwise, the model's accuracy will be comparable to that of subjects with more data. The system performance evaluation can measure the accuracy of the complete system in real-time when developing the real-time model. Fetts' law was used to calculate these results. This is used to evaluate the proposed system's objective performance [74].

6. COMPARATIVE ANALYSIS OF MOTION DETECTION TECHNIQUE AND DISCUSSION

This paper summarizes recent human-robot interaction research and development efforts in assistive and rehabilitation robotics. Several subdomains of assistive and rehabilitative robotic research are first identified. The background and trends of such advancements and the types of feature extraction domains employed by the technique are discussed. It has been discovered that feature extraction methods based on the Time domain can yield good results if the environment (e.g., temperature, humidity, and lightning) does not influence the recorded signals. While features-based Frequency domains perform well in real-time applications, they struggle to analyze brief EEG signals. It is difficult to choose the model order for AR spectral estimation. On the other hand, Feature-based parameter models can help reduce the constraints of spectral problems and improve the technique's accuracy by increasing frequency resolution. The feature-based Time-Frequency domain is superior for assessing rapid and transient signal changes and comprehending irregular data patterns, but it necessitates the selection of the appropriate mother wavelet. In addition, combining a large dataset with a robust feature selection strategy can improve the classifier’s performance.

7. CONCLUSION

The current methodologies and measures for assessing HRI states in biological signal analysis investigations are summarized in this paper. Different methods for estimating user states and the signals and procedures utilized to gather these signals are identified. For example, they must be processed and analyzed to prepare them for usage in machine learning algorithms. Furthermore, this research reviewed and analyzed the most important literature in the HRI perspective to measure the cognitive state by examining psychological and biological signals. After benefiting from the literature study, we want to develop a multi-module that uses analysis of biological data such as EEG and EMG to produce a robotic limb to assist patients with upper limbs. According to our research, the most prevalent feature extraction strategies have been presented with their benefits and drawbacks. According to a comparative study, accuracy varies depending on the situation. Finally, moving from feature engineering to feature learning is a good idea. On the other hand, DL improves representation through feature learning, which extracts high-level features from input data through multiple layers of processing blocks.

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