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A Review of Pattern Recognition Control Methods for Activation of Instrumented Wheelchair Power Assist Systems Based on sEMG Reading

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ABSTRACT – *Power-assisted wheelchairs have transformed rehabilitation technologies, providing people with disabilities more freedom and mobility. Signals from surface electromyography (sEMG) are vital for providing intuitive control over these systems. With an emphasis on classification accuracy, computational requirements, and suitability for instrumented wheelchair systems, this review assesses several pattern recognition techniques such as KNN, SVM, LDA, LSTM, Decision Trees, and Artificial Neural Networks (ANN). The study highlights the growing significance of hybrid approaches that combine pattern recognition techniques to increase robustness and precision. Even though KNN has the highest accuracy, methods such as LSTM and SVM are more effective and versatile, making them more appropriate for real-time applications. The results highlight the necessity of more research into personalized systems and hybrid models, which have huge potential to advance assistive technologies.*

KEYWORDS: Active safety, wheelchair, power assist system, machine learning, KNN, LSTM, SVM, electromyography signal

1. INTRODUCTION

Advancements in the field of neuroscience and technology have shifted the focus of control engineers toward integrating advanced techniques into assistive technologies for stroke rehabilitation. This evolution has not only aided but has significantly improved the quality of life of people with impairments. The breakthrough in the field is the progressive study and development of electromyogram (EMG) signals, which enable the recognition of muscular motion such as limb or arm movement using surface electrodes (Bonato et al., 1998).

One of the biggest innovations in the field of assistive technologies is instrumented wheelchair power assist systems, which are designed to provide users with enhanced maneuverability and control. These systems optimize neuromuscular mechanical fusion-based devices by implementing control techniques that match the user's needs and environmental conditions. This review focuses on comparing various pattern recognition control strategies, emphasizing their classification accuracy and suitability for integration into power-assisted wheelchair systems based on the analysis of sEMG readings and finding the best control technique with the highest accuracy and precision (Khushaba et al., 2016).

Pattern recognition with EMG is not a novel concept; it has been used widely in robotics, rehabilitation (e.g., prosthetic arms or limbs), Unmanned Ground Vehicles (UGVs), and many other fields. The basic idea is to use electrodes applied to the skin to extract surface EMG signals, process them, and use the results to make control decisions depending on the patient's goals and motions (Engel & Hildebrandt, 1974). This approach is usually referred to as Pattern Recognition, which allows instrumented wheelchair systems to function in real time by recognizing muscular motions and translating them into effective control actions (Atzori et al., 2014; Sidik et al.; Thongpanja et al., 2016).

Surface EMG (sEMG) is a cutting-edge technology in electromagnetic sensing that helps in interpreting user intentions and interaction with the surroundings. These readings are analyzed to recognize the patterns and develop control strategies that are accurate, robust, and intuitive (Kiran & Rani, 2017). By leveraging pattern recognition methods, sEMG facilitates the development of power-assisted systems like instrumented wheelchairs, offering users a more seamless and efficient rehabilitation process.

The purpose of this paper is to investigate several pattern recognition methods for power-assist systems and determine the most successful strategy after conducting a thorough investigation. The efficacy of these techniques is assessed using evaluation measures like robustness, F1 score, and classification accuracy. By evaluating the performance of these strategies, this study seeks to enhance usability and reliability, contributing to the advancement of rehabilitation technologies and fostering greater independence for individuals with mobility impairments (Engel & Hildebrandt, 1974).

2. LITERATURE REVIEW

Pattern recognition methods for control systems are rather complex but offer classification accuracy as high as 96.1% ± 4.3% (Zhang & Zhou, 2012). However, non-pattern recognition techniques using Arduino boards as the processor are more commonly used by researchers and engineers due to the simplicity and lower complexity compared to pattern recognition methods (Teikari et al., 2012). In the case of non-pattern recognition methods, typically a threshold value is used to trigger the control action and create a command. Despite the simplicity, these systems often exhibit low classification accuracy, making them less effective and unable to address the diverse needs of populations with varying disabilities.

In contrast, pattern recognition techniques are gaining traction due to the limitations of non-pattern recognition methods. This review provides a detailed analysis of pattern recognition techniques by comparing their accuracy and potential applications.

Pattern recognition methods focus on identifying Motor Unit Action Potential (MUAP) patterns from sEMG signals using advanced mathematical models. These methods enable real-time detection and make control decisions based on the identified patterns in the observed data (Requejo et al., 2015). They have emerged as efficient solutions for activating power-assisted instrumented wheelchairs, making the rehabilitation process smoother for diverse patient populations. Unlike conventional systems designed for specific disabilities, instrumented wheelchairs must interpret individual sEMG signals and tailor control responses accordingly (Day, 2002).

Factors such as gender, diet, and other physiological differences further distinguish each patient, necessitating a more personalized approach to wheelchair control (Engel & Hildebrandt, 1974). Pattern recognition systems excel in adapting to user-specific sEMG signals, addressing varying levels of mobility and dexterity. For instance, users with limited upper limb strength or varying motor functions require systems that interpret these differences accurately. By adapting to individual sEMG signals, pattern recognition methods provide personalized and efficient control aligned with each user's physical capabilities (Feng et al., 2019).

Many individuals with disabilities face limitations in generating the necessary force to propel a manual wheelchair. Power-assisted systems mitigate this challenge by reducing the physical effort required by integrating power assistance with sEMG data acquisition (Ghazali et al., 2016). These systems work by recognizing muscle movements during propulsion and utilizing real-time pattern recognition to ensure smooth, efficient assistance. This approach enhances usability for users with varied disabilities and increases the overall system flexibility. The integration of pattern recognition allows the system to learn from the user's movements and adjust power assistance levels, resulting in a more personalized and independent experience (Wong et al., 2020).

Pattern Recognition techniques are a game changer in the field of assistive technologies, enabling intuitive and efficient control systems by processing real-time data and making informed control decisions (Wong et al., 2020). While non-pattern recognition techniques such as the average method, confidence interval, and maximum class differentiation are simpler and less mathematically complex, they lack robustness and adaptability. Therefore, incorporating pattern recognition methods is essential to improve the accuracy and resilience of control systems, enabling them to cater to at least 90% of disabled patients and provide a better rehabilitation experience (VanSickle et al., 2000).

Widely used pattern recognition techniques include template matching, Artificial Neural Networks (ANN), Decision Trees (DT), k-th Nearest Neighbor (KNN), Long Short-Term Memory (LSTM), Linear Discriminant Analysis (LDA), and Support Vector Machines (SVM). These methods demonstrate the versatility and robustness needed to address diverse user needs and physiological differences, ensuring the system is available to more patients with fewer risks and able to differentiate tasks such as forward or backward stroke activities of the wheelchair (Baraldi & Blonda, 1999).

Surface electromyography (sEMG) is a technique used to capture electrical responses from muscles using electrodes placed on the body (Zaheer et al., 2012). Signals generated by muscle contractions are amplified, analyzed, and processed for control decisions. The sEMG control strategy includes pattern and non-pattern recognition techniques. While pattern recognition techniques are more robust and accurate, they require higher computational performance. In contrast, non-pattern recognition techniques operate on thresholds and often utilize low-performance processors like Arduino or microcontrollers. Despite their simplicity, some studies report classification accuracies above 90% for non-pattern recognition techniques (Rojas et al., 2018).

Despite the transformative potential of pattern recognition methods, challenges remain. These include computational demands, noise sensitivity, and the need for real-time adaptability. This review highlights the critical role of pattern recognition techniques in advancing power-assisted wheelchair systems, emphasizing their capacity to revolutionize assistive technologies and improve the quality of life for individuals with mobility impairments.

3. PATTERN RECOGNITION CONTROL METHOD

There is extensive literature on various control techniques for sEMG-based signals, though much of the research focuses on non-pattern recognition techniques. After thorough analysis, it has been observed that literature on pattern recognition techniques is comparatively scarce. However, studies have demonstrated that pattern recognition control techniques are more effective and accurate than non-pattern recognition methods, despite being more computationally demanding and complex (Phinyomark et al., 2011). The following Figure 1 gives an idea of how pattern recognition control methods work in general.

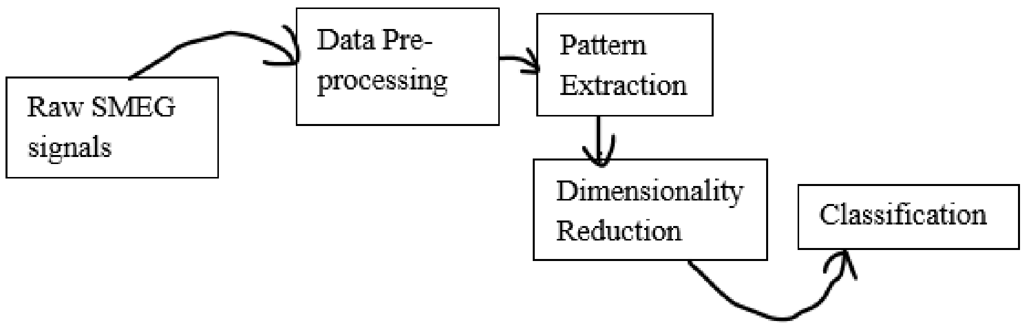

FIGURE 1: Block diagram of pattern recognition control methods

Pattern recognition control methods involve identifying trends or patterns in acquired data, such as sEMG signals from the subject's body. These techniques are highly efficient for real-time applications, although selecting the most suitable algorithm for the problem is crucial, as overly complex methods are not always optimal. Pattern recognition can be broadly categorized into three groups (Zhang & Zhou, 2012):

- **Statistical Techniques:** These involve using mathematical models to represent where the observed data points fit within the model observed data, focusing on probability density functions and decision boundaries to classify patterns. Statistical modeling is particularly advantageous for creating robust classifiers with high accuracy.
- **Structural Techniques:** Effective for multi-dimensional data, structural algorithms classify patterns hierarchically, dividing them into sub-classes and establishing relationships between features.
- **Neural Network Techniques:** Inspired by the human brain, these methods use interconnected neurons to learn from past data and make predictions. Neural networks are particularly useful for processing complex, nonlinear datasets.

For the control of instrumented wheelchairs, statistical algorithms are often the most practical due to their balance of accuracy and computational efficiency. The following literature gives a short overview of various statistical algorithm techniques:

3.1 Artificial Neural Network (ANN)

ANN is one of the most widely accepted pattern recognition approaches for control systems. As it has already been used for various prosthesis projects and has proved to be a very useful control method, it is still not very common for electrically powered instrumented wheelchairs. The idea is not very common, probably because of its poor performance when compared with the classification accuracy of the other available pattern recognition techniques for the wheelchairs. According to the literature, another classifier named BAPNN that used the gradient descent technique along with the root mean square was tested and used to identify the patterns (Rajesh & Reddy, 2009). It was proved to have a classification accuracy of 97.5%, which will be discussed in Section 5 of the research paper.

3.2 K-th Nearest Neighbor (k-NN)

K-NN is a non-parametric instance-based learning algorithm that uses statistical techniques to notice the similarities between the data points in the given dataset. There are two different key aspects of k-NN for pattern recognition, such as classification based on distance (Manhattan or Euclidean distance) and proximity-based classification. The decision boundary in the case of the k-NN algorithm is created based upon the statistical analysis of how data points are dispersed throughout the feature space. Therefore, this technique helps in geometric pattern recognition.

3.3 Decision Trees (DT)

Decision trees are used to identify patterns to make decisions. Decision trees split the datasets into sub-trees, dividing them into categories based on the features using a tree-like structure. The tree continues recursively, starting from a root node and splitting at various internal nodes until a leaf node is reached. This technique can be regarded as a powerful pattern recognition technique that identifies patterns depending upon the features and hence helps in making decisions. It can identify non-linear relationships in the datasets.

3.4 Support Vector Machine (SVM)

A Support Vector Machine (SVM) is a very powerful supervised learning algorithm using statistical techniques widely used for classification and pattern recognition tasks. It works by finding the optimal hyperplane that best separates data points of different classes in a high-dimensional space and helps in deciding the decision boundary. The goal of this algorithm is to maximize the marginal distance between the hyperplane and the nearest data points from each class, known as support vectors. To improve the classification accuracy of the model, the maximized decision boundary is the key aspect. SVMs are particularly effective for handling complex datasets, especially when there is a clear margin of separation between classes. They can also work with non-linearly separable data by using kernel functions to map the data into higher dimensions, making SVMs versatile for pattern recognition.

3.5 Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis is a statistical technique particularly used for classification and dimensionality reduction. It works by finding the linear combination of features that can separate and distinguish between two or more classes. The main goal of this algorithm is to maximize the intra-class variance and minimize the inter-class variance. The main assumption is that the data points for each class follow a Gaussian Distribution that has similar covariance matrices but different mean values. LDA is often widely recommended due to its simplicity, high efficiency, lower computational cost, and ability to reduce the risk of overfitting in high-dimensional datasets (Zhou et al., 2017).

3.6 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network (RNN) designed to model temporal dependencies and patterns over extended periods. LSTMs are particularly well-suited for sequential data, such as sEMG signals, where the temporal relationships between data points are critical for accurate classification. By using memory cells, LSTMs can retain important information over long sequences while discarding irrelevant data, making them effective for capturing dynamic and evolving patterns in motor control tasks like wheelchair assistance.

All the above-mentioned techniques have their own unique advantages and limitations, underscoring the importance of selecting the most appropriate technique based on the specific requirements of instrumented wheelchair control systems. A comprehensive review and comparison of these methods will be presented in subsequent sections. This comparison aims to identify the most suitable pattern recognition technique for ensuring smooth wheelchair operation, emphasizing metrics like classification accuracy, precision, and robustness.

4. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network is one of the pattern recognition approaches that have been under development for instrumented wheelchairs. Despite their computational complexity, ANNs have shown potential for achieving high classification accuracy. However, their adoption in this field has been limited historically due to poor performance in earlier studies. In rehabilitation and medical applications, security and reliability are critical, and any method falling short in these areas has been deemed unsuitable (Yousif et al., 2016).

Recent developments have brought attention to techniques like the Conic Section Function Neural Network (CSFNN), which analyzes patterns in data collected from muscles such as the forearm, shoulder, and elbow. Although the accuracy of these systems has not yet reached optimal levels, there is significant potential for improvement and integration into wheelchair control systems. For example, CSFNN can process patterns to trigger control actions, such as moving forward, backward, or turning (Ozyilmaz et al., 1999).

ANNs generally consist of three layers: an input layer, one or more hidden layers, and an output layer. It can be extended by adding more nodes to the hidden layers, which can improve classification accuracy, but this increases computational complexity and costs. CSFNN offers high accuracy by using conic section functions to detect subtle differences in captured patterns. This ability aids in recognizing user intent and making controlled decisions.

The potential challenges with the CSFNN include training complexity, mathematical complexity, noise sensitivity, and quick real-time data acquisition. These ANNs need to undergo more extensive research and evaluation for the application of control systems.

The quality and efficiency of ANN can be observed by recent studies exploring ANN to control wheelchairs, shows a promising results (Rajesh & Reddy, 2009). Rajesh employed ANN for hand gesture recognition using sEMG and achieved a success rate of 97.5% with four different gestures. Similarly, another study **Error! Reference source not found.**had implemented the Recurrent Neural Network (RNN), one of the variants, to recognize 12 hand gestures and achieve an accuracy of 96.5% (Adebayo et al., 2021). These real-time applications further showcase the applicability for more intuitive wheelchair control.

Even though ANN do may pose significant computational complexity, it manages to showcase robustness in extracting features from noisy EMG signals that exist in controlling motorized wheelchairs (Adebayo et al., 2021; Rajesh & Reddy, 2009). The versatility of ANNs to adapt to different feature extraction techniques such as statistical measures or wavelet transform secures their utility in this application.

5. K-TH NEAREST NEIGHBOUR

As a classifier, K-NN helps make decisions based on the patterns identified in real-time sensor data. According to Bhaduri, K-NN was employed in a system designed for rehabilitation, using EEG signals to classify upper and lower limb movements (Bhaduri et al., 2016). The system achieved high classification accuracy with K-NN and the Naïve Bayes classifier together providing 90% accuracy in recognizing limb movements. This demonstrates K-NN's potential for real-time control systems, particularly in prosthetic devices.

However, the complexity of integrating real-time signals from multiple sources, such as shoulder and elbow muscles, poses challenges for K-NN. As noted in (Oskoei & Hu, 2007), K-NN performs best when used in combination with hybrid techniques that combine both pattern and non-pattern methods.

The potential of KNN in real-time applications for wheelchair control can be demonstrated in one example of a study by Iqbal et al. (2023) that expresses an impressive offline accuracy of 99.74% for hand gesture recognition with sEMG signal in a real-time application. The study shows accurate classification patterns even in noisy environments, showcasing seamless wheelchair maneuvering.

Though the significant strengths in simplicity and accuracy were demonstrated, challenges pose on KNN's dependency on the choice of the 'k' value and computational inefficiency for large datasets. However, KNN's effectiveness can be further proven when paired with other methods, such as ensemble techniques, to improve robustness and dynamic environment handling (Iqbal et al., 2023).

6. DECISION TREES

Decision trees are also one of the most common machine learning classifiers used for pattern recognition due to their simplicity and high accuracy. Several algorithms enhance Decision Trees' performance, such as Classification and Regression Trees (CART), Chi-Squared Automatic Interaction Detection (CHAID), and Iterative Dichotomizer 3 (ID3). These algorithms enable feature extraction and classification for control decisions, making Decision Trees particularly effective in recognizing EMG signal patterns with high accuracy (Yaman et al., 2011).

Decision Trees classify data using either a depth-first greedy approach or a breadth-first approach, continuing iteratively until all nodes are correctly categorized into relevant groups or classes (Yaman et al., 2011). The recursive nature of these classifiers strengthens their capability to predict over time as the training process refines the model. The classification process in Decision Trees occurs in two major phases: Tree Building and Tree Pruning. During Tree Building, impurity functions are used to optimally split data for accurate predictions, while Tree Pruning reduces overfitting and improves model generalization.

According to Yaman et al. (2011), Decision Trees achieved a 94% success rate in evaluating EMG signals for myopathic and neuropathic patients using the C4.5 algorithm. The analysis of the tree-building process took just 0.2 seconds, with a tree size of 59 and 30 leaves giving the best result.

Similarly, a study by Afrin et al. (2022) combined Decision Trees with Random Forest, achieving an accuracy of 95.42% for hand gesture-based wheelchair control using sEMG signals collected from forearm muscles. A recent study by Iqbal et al. (2024), which applied Decision Trees, achieved an accuracy of 97.77% in recognizing hand gestures for wheelchair control.

These research studies show that Decision Trees have faster learning time and give higher classification accuracy for muscle-related diseases, showcasing that it is one of the most suitable techniques for making control decisions. Their straightforward structure and interpretability further enhance their appeal.

However, challenges such as overfitting and scalability remain, particularly when Decision Trees were introduced with large, high-dimensional datasets. Ensemble methods, such as Random Forest or Gradient Boosting combined with Decision Trees, have been shown to mitigate these issues while further enhancing the classification accuracy (Afrin et al., 2022).

7. SUPPORT VECTOR MACHINE (SVM)

Recent research highlights SVM as a powerful and accurate classifier compared to traditional Artificial Neural Networks such as CSFNN and BPANN. SVMs demonstrate lower computational complexity, making them a good choice for real-time applications. Several studies have used SVM for the control of the wheelchair using EMG or sEMG signals for the signal control and operation.

Oskoei and Hu (2008) developed a pattern recognition-based control for an electrically powered wheelchair that uses SVM as the classifier to classify the signal time-domain features. The system used EMG signals collected from four forearm locations via surface electrodes placed on specific muscles. The SVM model classified time-domain features such as mean absolute value, wavelength, and zero crossing to create an optimal boundary in the feature space of the training data. The support vectors, or the informative samples, were identified to construct the decision function for precise control of a virtual joystick for wheelchair manipulation (Oskoei & Hu, 2008).

A study by Iqbal et al. (2024) demonstrated the versatility of SVM in use-independent systems. In the research conducted on hand gesture recognition using RMS features from sEMG signals, a Multi-Class SVM (MC-SVM) achieved an accuracy of 99.05%. This study further highlights the ability of SVM-based classifiers to adapt to different user profiles without retraining, making them ideal real-world assistive technologies.

The experimental results in various research projects and literature have shown that the use of SVM as a classifier is recommended as a pattern recognition control technique for the control system for making informed and control decisions with the highest classification accuracy and robust performance.

8. LINEAR DISCRIMINANT ANALYSIS (LDA)

Linear Discriminant Analysis (LDA) is a statistical pattern recognition method that has been widely applied in control systems for assistive devices. Englehart and Hudgins (2003) described the pattern recognition technique for controlling the hand and wrist movement for an elbow limb prosthesis. The approach continuously relied on the extraction of the pattern and classification of the muscle signals enabling movement, focusing on four different types of motions. Time-domain features were utilized, with LDA serving as the classifier. The system's performance was evaluated based on classification error rates.

In this context, LDA proved to be an effective pattern recognition classifier, enabling the system to determine the origin of muscle signals and make accurate control decisions. The study further highlighted the suitability of LDA for myoelectric control, where each class corresponded to a specific degree of freedom in the prosthetic limb. With a classification accuracy of 94%, the approach validated LDA’s robust performance for a four-class problem, albeit limited to signals from wrist, limb, and elbow muscles. This underscores LDA reliability in systems requiring precise signal classification for control decisions.

Further studies implementing LDA's applicability in wheelchair control. For instance, in a study by Wajahat et al. involving neck muscle signals for controlling a powered wheelchair, LDA achieved an accuracy of 75.5% for distinguishing neck movements (Gondal et al., 2022). This demonstrates its feasibility for muscle-driven assistive technologies, although its performance may be affected by the complexity of real-time scenarios.

Moreover, its computational efficiency and simplicity make LDA particularly suitable for low-power embedded systems, allowing it to handle tasks like real-time signal classification without significant latency (Gondal et al., 2022). While it may not outperform more advanced classifiers like SVM in terms of accuracy, its robustness in handling smaller datasets and reduced computational demands are notable advantages.

9. LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that overcomes the vanishing gradient problem that is common to RNNs. LSTMs are ideal for tasks requiring temporal dependency and long-term knowledge retention.

Welihinda's research highlights the use of LSTM in wheelchair control for decoding user intentions from forearm EMG signals and EEG signals (Welihinda et al., 2024). The LSTM model achieved a higher accuracy (97.3%) compared to the Quadratic SVM (86.67%), showcasing its ability to better capture temporal patterns in sequential data. This makes LSTMs well-suited for applications involving dynamic and real-time signal processing, such as gesture recognition and assistive device control.

While Zhang demonstrates the combination of LSTM with CNN to process periocular EMG and EEG signals for hybrid wheelchair control (Zhang et al., 2024). The LSTM component is used to model temporal dependencies in the signals, enhancing the robustness of the control system by integrating sequential information over time. In this study, the combination of LSTM and CNN achieved accuracy of 98.7%, highlighting the potential of hybridization of classification with LSTM.

10. COMPARATIVE ANALYSIS OF PATTERN RECOGNITION METHODS

A comprehensive overview of several pattern recognition techniques applied to sEMG-based control systems reported between 2014 and 2024 is given in Table 1. The key metrics such as accuracy, precision, recall, F1 score, and computing efficiency are used to assess these approaches' performance. The main objective is to determine the best methods for use such as wheelchair control and rehabilitation.

Among the analyzed methods, K-Nearest Neighbor (KNN) achieves the highest classification accuracy of 99.74%. This illustrates how well it works in situations where precision is needed, but computational inefficiencies may limit its scalability for larger or real-time applications. Following closely is Support Vector Machine (SVM), with an accuracy of 99.05%, showing its robustness across diverse applications due to its adaptability and efficiency.

The LSTM + CNN hybrid model also demonstrates remarkable performance with 98.17% accuracy, highlighting its ability to manage both temporal and spatial data, making it ideal for dynamic applications. Decision Trees (DT), with 97.77% accuracy, provide simplicity and interpretability, making them suitable for real-time systems. Even though artificial neural networks (ANN) have somewhat lower accuracy levels (90.2% to 97.5%), they are nevertheless useful in some situations when the data is well-defined but not as noisy or dynamic.

KNN's exceptional accuracy makes it a top choice for precision-critical applications, but its computational inefficiency can hinder real-time or large-scale implementation. SVM is robust for user-independent and adaptable systems, though it may not handle large-scale, real-time datasets as effectively as neural networks.

TABLE 1: Comparison between different types of pattern recognition methods

Method	Muscle Point	Samples	Performance Metrics	Feature Extraction Technique	Application	Published Year
LSTM + CNN	Periocular muscles	Training: 4,067 samples (3 volunteers) Testing: 1,288 samples (3 volunteers)	Accuracy: 98.17% Loss Function: 0.05 Recall: 0.97 F1 score: 0.97	CNN extracts spatial, LSTM extracts temporal, combined for classification.	Rehabilitation wheelchair control	2024 (Zhang et al., 2024)**Error! Reference source not found.**
LSTM			Accuracy: 95.19% Loss Function: 0.1194	Extracts temporal dependencies for classification.		
CNN			Accuracy: 97.85% Loss Function: 0.09	Extracts spatial features for classification.		
ANN			Accuracy: 90.7% Loss Function: 1.8347	Basic classification without specialized feature extraction.		
LSTM	Forearm muscles	6 participants: 5 gestures (~258 samples/gesture)	Accuracy: 97.3% Precision: 0.89	Time-domain features (e.g., MAV, RMS, ZC, VAR)	Navigation of powered wheelchairs	2024 (Welihinda et al., 2024)
Quadratic SVM			Accuracy: 86.67% Precision: 0.89			
MC - SVM	Forearm muscles	6 participants: 5 gestures	Accuracy: 99.05% Precision: 99.15% F1 score: 98.81% Recall: 98.47%	Time-Domain features: Root Mean Square (RMS)	Hand gesture-based wheelchair control	2024 (Iqbal et al., 2024)
DT			Accuracy: 97.77% Precision: 97.11% F1 score: 97.15% Recall: 97.19%			
ANN - MLP	Forearm muscles (4 electrodes)	50,925 rows reduced to 254 features; 5 motion labels	Classification accuracy: 90.2% (five-fold cross-validation)	Mean Absolute Value (MAV)	Control of wheelchair movements (forward, backward, left, right, stop)	2014 (Mahendran, 2014)
DT	Forearm muscles (8 electrodes in armband)	• 12 healthy participants, 7 SCI patients • Training: 18,000 samples • Testing: 10,500 samples	Accuracy: 95.42%	Mean Absolute Value (MAV)	Hand gesture-based control of powered wheelchair	2022 (Afrin et al., 2022)
RF			Accuracy: 95.42%			
KNN			Accuracy: 94.00%			
SVM			Accuracy: 81.00%			
ANN			Accuracy: 93.14%			
QDA	Neck muscles	6 participants: 2 neck movement	Accuracy: 81.1%	Time and Frequency Domain Features: Mean, Variance, RMS, Skewness, Kurtosis, Kean Frequency	Control of wheelchairs using neck movements	2022 (Gondal et al., 2022)
LDA			Accuracy: 75.5%			
DT			Accuracy: 76.5%			
SVM			Accuracy: 76.5%			
LSTM	Forearm muscles	8 participants: 12 hand gestures	Accuracy: 96.5%	Band-pass filtering (20–500 Hz), Normalization	Hand gesture-based motorized wheelchair control	2021 (Rajesh & Reddy, 2009)
KNN	Forearm muscles	Not specified: multiple trials for hand gestures	Accuracy: 99.74%	Not explicitly mentioned	Real-time hand gesture-based wheelchair control	2023 (Iqbal et al., 2023)
ANN	Forearm muscles	20 participants: 4 gestures	Success rate: 97.5%	Wavelet Transform, Statistical Features: RMS, Entropy	Control of wheelchair through hand gestures	2015 (Adebayo et al., 2021)

The LSTM + CNN hybrid model is highly suitable for applications like rehabilitation wheelchair control, where spatial and temporal data integration is crucial. Decision Trees and Random Forests offer efficiency and interpretability but may struggle with scalability in high-dimensional datasets. ANN demonstrates potential for specific gesture-based control tasks, but its sensitivity to noise and data variability may limit its effectiveness in dynamic scenarios.

11. CONCLUSION

In conclusion, this review investigates how pattern recognition techniques are used to activate sEMG-based instrumented wheelchair power-assist systems. The comparative study shows that methods such as KNN, SVM, LDA, and LSTM show different strengths based on application-specific requirements, computational complexity, and classification accuracy. Among these, hybrid strategies that combine two pattern recognition techniques have a big potential to improve robustness and flexibility. Although KNN has the best classification accuracy, techniques like SVM and LSTM offer a balance between speed and accuracy that makes them suitable for real-time applications.

Future research should concentrate on improving hybrid models and tackling issues like noise sensitivity and computational demands, especially for dynamic rehabilitation settings. These approaches have tremendous potential for developing customized and user-friendly wheelchair control systems, which would increase the mobility and independence of people with disabilities.

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