ISSN (e): 2250 – 3005 || Volume, 14 || Issue, 4|| Jul. - Aug. – 2024 ||
International Journal of Computational Engineering Research (IJCER)

Enhancing Hand Gesture Recognition: The Ideal Channel Configuration for Low Complexity and High Accuracy

Davinder Kumar,
Research Scholar,
School of Electronics and Electrical Engg., Lovely Professional University, Punjab1
Email: davinderthakur078@gmail.com

Dr. Anuj Jain
Professor, School of Electronics and Electrical Engg., Lovely Professional University, Punjab.
*Email: a1978jan@**gmail**.com*
ORCID:0000-0002-5740-5127

Dr. Aman Ganesh,
Professor, Department of Electrical Engineering, Maharishi Markandeshwar (Deemed to be University),
Mullana-Haryana
Email: aman.ganesh@mmumullana.org,
ORCID:0000-0002-7950-1064.

Abstract
Due to its numerous uses and capability to communicate effectively with machines via human-computer interaction, Hand Gesture Recognition (HGR) systems have attracted a lot of attention in recent times. In this paper, we have reviewed and analyzed the importance of HGR systems in various application of real world. The main focus of this paper is to determine the ideal number of channels for detecting hand gesture effectively with low complexity. For this reason, we analyzed and compared the performance of single and multiple channels based HGR systems in this paper. Through our analysis, we came to conclusion that single channel based HGR model undergoes through noise issues while using more than 4 channels leads to high complexity and computational time. To overcome this, some researchers have proposed model in which they have used only two channels for detecting Hand gestures. These models showed enhanced accuracy results with low complexity and hence more work must be performed in this area.

Date of Submission: 05-07-2024 Date of acceptance: 18-07-2024

I. Introduction

Numerous modalities are used in human communication. Characteristics of the expression, such as temporo-spatial, visual, structural, and emotional aspects, seem to be implemented in close cooperation by words, gestures, facial expressions, and bodily movements. One of the key methods in human-computer interface (HCI) is hand gesture recognition. Recognition of hand gestures has a wide variety of uses, including teleoperation, entertainment, and medicine. The relative flexure of the user's fingers is required for hand gestures, which frequently contain information that is too ethereal for machines to comprehend. A hand-gesture to voice system can help the deaf or non-vocal individuals live better lives, which is a significant application of hand gesture recognition. Rehabilitation engineering and prosthetics are two more important applications. Mechanical sensors, vision-based systems, and electromyograms are a few of the regularly used methods for hand recognition [1-2]. In addition to being non-invasive, electromyograms have the benefit of being simple to record. An easy solution for controlling the prosthesis is surface electromyography (sEMG), which is the electrical manifestation in the activity of contracting muscles and intimately associated to the muscle contraction. Surface electromyography, also known as sEMG, uses surface sensors to record the electrical activity of skeletal muscles. Two states of a skeletal muscle are combined to produce this electrical activity. A skeletal muscle is in its initial state when it is at rest when each of its muscular cells (or muscle fibres) has an electric potential of about -80 mV [3]. In order to activate a neuromuscular junction, a motor neuron sends two intracellular action potentials in opposition to one another wherein, they are spread by depolarizing and repolarizing every muscle fibre individually [4]. The term "motor unit action potential (MUAP)" is used to define sum of all intracellular action potentials generated by the muscle fibres that make up a motor unit. As a result, the EMG is a linear summation of many trains of MUAPs when a skeletal muscle contract. Muscle contractions come in static and dynamic varieties. Static contractions occur when the lengths of the muscle fibres remain constant and the joints are immobile, yet the muscles still contract, for instance when a person holds their hand steady or makes the peace sign. A dynamic contraction occurs when the lengths of the muscle fibres change and the joints move, like when a person waves their hand in greeting. The two distinct contraction types previously mentioned can be used to represent the EMG signals as a stochastic process. Firstly, the EMG exclusively depends on muscle force [5], and the mathematical model for a static contraction (MMSC) is a stationary process because the mean and covariance stay about the same across time. Consider (1):

$EMG(t) = \sum_{i=1}^{N} S_i(t) * m_i(t)$--------(1)

Wherein N is the total number of active MUs, S i (t) is the train of impulses that represents every MU's active moments, m i (t) represents the MUAPs for every MU, and * stands for convolution. When conditions like muscle exhaustion and temperature have an impact on the EMG, the MMSC can be seen as a non-stationary procedure. Second, the mathematical model for a dynamic contraction (MMDC) is a non-stationary process, and its mathematical model is similar to the amplitude's modulation (AM modulation):

EMG(t) = a(t)w(t) + n(t)-------------(2)

wherein w(t) is a unit-variance Gaussian process indicating the stochastic aspect of the EMG (i.e., carrier signal), n(t) is the noise from the sensors and biological signal artifacts, and a(t) is a function that reflects the intensity of the EMG signal (i.e., information signal).

Surface electromyography (sEMG), in its simplest form, is the spatial and temporal superposition of weak bioelectrical signals produced by the muscular nerve cells while muscle contraction [6-7]. Through the skin surface electrodes, it is gathered and recorded. According to earlier studies, motions are often detected by accelerometers, capacitive methods, or proximity sensors placed on various body areas. These methods call for the users to move their limbs conspicuously, which can be uncomfortable and considered inappropriate in social situations. Electromyographic (EMG) signals, on the other hand, can communicate information regarding isometric muscle activity, which is the activity associated with very slight or no movement at all. As a result, it makes it possible to define a class of "subtle" or "motionless gestures" that can be applied to the creation of covert, private mobile interfaces [8]. The sEMG signal has advantages over standard EMG signal acquisition in that it doesn't need puncturing muscle tissue with an electrode, and it's simpler to gather. Additionally, it is crucial for games, the understanding of sign language, and other HCI systems. The forearm's numerous flexors and extensors, which are involved in every hand position, are, therefore, a complex mix. Due to the close proximity of the muscles in the forearm, any myoelectric activity detected at one muscle site also includes activity from other muscles, a phenomenon known as cross-talk. When there is little (subtle) muscle activation, crosstalk and noise have a significant negative impact on the signal strength. When comparing different participants, this is accentuated even more because each individual's level of training, subcutaneous fat layer thickness, and muscle size will vary. However, it is difficult to model or generalize this mixing of electrical activity from many muscles to produce the surface EMG (sEMG) signal. Low levels of contraction make it even harder to extract relevant information from this type of surface EMG because of the low signal-to-noise ratio. EMG activity is scarcely distinguishable from the background activity at low levels of contraction. Furthermore, EMG needs to be broken down to identify the activity of particular muscles in order to appropriately categorize the movement and gesture of the hand with greater precision. Because there is minimal to no prior knowledge of the muscle activity and there is spectral and temporal overlap between the signals, the issue can be resolved using blind source separation (BSS) or infrared spectroscopy (ICA). Furthermore, the goal of the sEMG signal survey was to create methods for classifying and recognizing patterns in order to accurately detect various hand movements [9, 10]. Applications for classifying hand movements with the aid of sEMG signals are numerous and include operating prosthetic hands, human computer interfaces (HCI), and therapy robots, among others. [11].

Numerous techniques and algorithms, including ANNs, fuzzy classifiers, neuro-fuzzy classifiers, and other probabilistic-based techniques, have been developed in order to achieve high classification results. EMG signals have a higher level of noise complication than other bio-signals. Motion artifacts, built-in hardware, electromagnetic radiation, etc. are all examples of noise sources [12]. It is even harder to classify multiple classes from sEMG. It is challenging to establish an explicit relationship between the measured signals and a motion command because the nature of the EMG signal is complicated and extremely nonlinear. Pattern recognition algorithms are crucial for separating and identifying the functionality of various sEMG signals from their derived features. The quantity of channels employed in HGR systems is crucial in this context. For identifying various forms of hand motions, the majority of researches only use one channel. Using a single channel sEMG, a novel method for determining finger motions is shown in example [13]. But, the low reliability of such approaches is a challenge. Due to the low amount of contraction (flexion) in these systems and the near proximity of the corresponding muscles, cross talk and a very poor signal to noise ratio (SNR) are the two main problems. Multichannel EMG research has been conducted to get over the drawbacks of single channel sEMG-based systems. The effectiveness of motion categorization is enhanced by multichannel EMG signals. Multichannel is beneficial, as demonstrated by some earlier research like [14]. Average classification accuracy will rise as the number of channels rises; however, once there are more than four channels, processing a huge data set of features becomes challenging. Although the EMG multichannel method has benefits for categorization, it is both bulky and complicated. As a result, it's crucial to select a precise number of channels in the HGR system that can reliably obtain EMG signals while simultaneously reducing system complexity. In this regard, we will examine some of the recently suggested HGR systems where authors have utilized single or multiple channels to acquire data on EMG signals.

The coming up sections of this review paper discusses number of single and multiple channels used for data collection. To have a better understanding and conclusion, we have also put comparison tables at the end of each category for reviewing their performance. Also, after studying multi-channel HGR systems, we will analyze which model is frequently used by researchers and accordingly discuss more about it.

Single channel based HGR systems

In this section, we are going to discuss only those HGR systems in which authors have used single EMG signal for collecting necessary information about hand gestures. As mentioned earlier these systems do have low complexity but due to the noise and other factors, it is difficult to extract sEMG signal from one channel. Here, some of the renowned literatures have been discussed that use only single ENG channel.

To begin with. the authors in [15], proposed a straightforward, quick, and inexpensive technology that can distinguish up to four gestures from a single channel surface EMG signal. Hand shutting, hand opening, wrist flexion, and double wrist flexion are examples of gestures that were recognized. A prosthetic terminal was operated with these gestures based on predetermined grasp positions. The authors demonstrated how these four motions may be identified and classified using a high-dimensional feature space and SVM technique. The calibration process took just 30 seconds, and good classification accuracy over multiple test sessions without having to redo the calibration process proved that it was session independent. In [16], authors described a novel method for classifying the single channel sEMG to detect low-level hand movement. Because of its ease of use, low cost of computing, and efficiency, single channel sEMG analysis was favored over multi-channel. To categorize and analyze the sEMG signal more effectively, wavelet processing and an artificial neural network (ANN) classifier were used. Similarly, in [17], the authors discussed how to recognize and categorize hand movements made by healthy participants in real time. Therefore, the study of the best feature and classifier selection for the intended hand movements was described. The LabView platform was used to categorize the two types of hand movement, relaxed hand, and closed hand. Surface electromyography (sEMG) data was collected for this reason by utilizing a single channel electrode. Mean, variance, kurtosis, and skewness were taken out of the signals as statistical time domain characteristics that serve as the signal's classification features. Initially, sophisticated classifiers, such as SVM and KNN classifiers, were used for offline classification. The findings demonstrated that the suggested model is a reliable and accurate way to categorize hand movements, with an offline classification accuracy of about 96.58%. In [18], the authors utilized OPENBCI to collect data on two hand motions and then decode the signal to identify the different gestures. Three electrodes were placed on the participant's forearm to retrieve the signal, which was then sent in a single channel. After applying a Butterworth bandpass filter, they decided on a creative approach to gesture action segment detection. The authors created an approach based on the Hilbert transform to establish a dynamic threshold and identify the action section rather than the moving average approach, which was based on calculating energy. Every action portion has four features that were retrieved, creating feature vectors for categorization. Depending on a modest number of samples, they compared K-nearest neighbors (KNN) with support vector machines (SVM) during the classification phase. According to experimental findings, the SVM method has had an average recognition rate that was 1.25 percent greater than the KNN algorithm but took 2.031 seconds less time. Additionally, in [19], a time-domain single-channel sEMG enveloped signal feature-based gesture identification system was investigated. Firstly, a preprocessing circuit was used to obtain the sEMG envelope signal. Next, researchers located every valid activity segment using the enhanced approach of valid activity segment extraction and then retrieved 15 characteristics from each valid activity section. Moreover, they determined the correlation coefficient's absolute value between every attribute and the desired values. The 14 features were kept after the feature with the lowest correlation coefficient was eliminated. They converted the 14-dimensional feature into a 2-dimensional feature space using the PCA dimensionality reduction approach. To accomplish the classification of five different gesture kinds, researchers employed the enhanced KNN method with the soft margin SVM algorithm. Utilizing the enhanced KNN method and the soft margin SVM algorithm, they achieved gesture recognition rates of 75.8 and 79.4%.

Moreover in [20],authors suggested a technique for classifying five different hand gestures—the pinch, the spread-fingers gesture, the fist, the wave in, and the wave out—using single-channel electrodes. Preprocessing, data segmentation, feature extraction, and classification were the four processes that make up the suggested methodology. A muscular activity detection technique was used during the preprocessing stage to eliminate dataset rest areas. An overlapped windowing approach was used during the data segmentation process to divide the primary window into smaller ones. One portion of the features was observed from the aforementioned sub-windows during the feature extraction stage. Additionally, temporal domain properties of the unprocessed surface electromyography signals were recovered. Furthermore, a sub-window observation was labeled for classification using a model of an artificial neural network. The proposed approach had a 91.3% accuracy rate, according to experimentation. In [21], the authors proposed a single channel electromyography blind recognition approach based on watermarking. To prevent intricate circuit connections, unreliable hardware, and noise that accompanies surface electromyography (sEMG) signals; single channel independent component analysis was used. In order to address the issue of blind source separation disorder, embedded watermarking was utilized. For the classification of sEMG characteristics, an autonomous neural network and some eigenvectors were used. The categorization findings could also be used to identify hand movements. The host sEMG signals were converted into wavelet domain and the synchronization codes were incorporated in order to take time-scale synchronization attack into account. The experiment findings revealed that the model put forward in this study was robust against the majority of signal processing techniques and was capable of precise hand gesture recognition. Moreover, in [22], authors stated that Ultrasound is a viable method in the field of human-machine interface (HMI) since it could detect volumetric changes in contracting muscles. In contrast to US imaging (B-mode US), the signal from a static single-element US transducer, known as A-mode US, was more practical and affordable for use in wearables and other practical applications. In this work, one of the most widely used signal modalities for recognizing wrist and finger gestures was compared to single-channel surface electromyogram (sEMG) signals in terms of performance. Results showed that, whereas sEMG performed better than A-mode US in detecting the Rest state, A-mode US outperformed sEMG in recognizing six out of nine motions. Researchers also showed that the benefit of A-mode US over sEMG for gesture detection was owing to its improved capacity to identify information from deep musculature via feature space analysis. This work demonstrated the distinct complementing benefits of employing sEMG and A-mode US, demonstrating the potential for combining the two signal modalities for gesture recognition applications.

Table 1: Comparison table for Single channel based HGR systems

References	Work done	Channels Used	Outcomes
[15]	Proposed an effective HGR system that was based on SVM and identified four gestures.	One	good classification accuracy over multiple test sessions
[16]	Proposed a novel method for identifying low level hand movements that was based on wavelet processing and ANN	One	Effectively detected low level hand movements
[17]	Proposed a HGR system that was based on SVM and kNN for detecting two types of hand movements	One	classification accuracy of about 96.58%.
[18]	Proposed a KNN and SVM based HGR system in which data was collected by using OPENBCI.	One	SVM method has had an average recognition rate that was 1.25 percent greater than the KNN algorithm
[19]	Proposed a time-domain single-channel sEMG enveloped signal feature-based gesture identification system that was based on enhanced KNN and Soft margin SVM	One	gesture recognition rates of 75.8 and 79.4% was attained by Enhanced KNN and soft margin SVM
[20]	Proposed an ANN based HGR system that was able to detect five different hand gestures	One	proposed approach had a 91.3% accuracy rate
[21]	proposed a single channel electromyography blind recognition approach based on watermarking	One	Robust and precise

After analyzing the literatures, it has been seen that majority of the works that are using single channel undergo through various issues like noise addition by machines, background etc., which lowers the accuracy of system. Therefore, in order to boost the accuracy and performance of current HGR models, multi-channel EMG channels must be used. in the coming up section of this paper, we have discussed some of the recently proposed multi-channel based HGR systems.

Multi-Channel based HGR System

In order to overcome the limitations of single channels based HGR system, the authors in [23], developed an HRM model through unique hybridization of two parallel routes (one convolutional and one recurrent), coupled via a fully-connected multilayer network acting as the fusion center and offering robustness across various circumstances. The hybrid design was specifically suggested to treat temporal and spatial variables in two parallel processing channels and to improve the model's discriminative capacity in order to lower the necessary computational complexity and build a compact HGR model. In order to provide a compact architecture, researchers created the TCNMTCNM. It's vital to note that a deep model's efficiency, particularly its memory usage and parameter count, was as significant as the precision that can actually be achieved in practice. Due to the use of unique dilated causal convolutions that gradually expand the network's receptive area and utilize the use of shared filter parameters, the TCNM requires substantially less memory during training than the HRM. For evaluation reasons, the NinaPro DB2 dataset was used. The suggested HRM performed noticeably better than its competitors and achieved a remarkable HGR rating of 98.0198.01%. The TCNM performed better than conventional solutions while requiring less processing power thanks to its accuracy of 92.592.5%. In [24], an electromyography (EMG) signal collection was presented for use in research on human-computer interaction. Four-channel surface EMG data from 40 people, evenly split between the sexes, were included in the dataset. The following gestures were included in the data: neutral or resting position; extension or flexion of the wrist; ulnar or radial deviation of the wrist; grasp; abduction or adduction of all fingers; supination or pronation; and gripping. Data were obtained with the BIOPAC MP36 device employing Ag/AgCl surface bipolar electrodes while imitating 10 different hand gestures in 4 forearm muscles. Five repeating cycles of 10 hand motions were included in every participant's data. Before beginning the signal capturing process, participants were asked to complete a demographic survey. For the purpose of creating EMG-based hand movement controller systems, this data could be used for recognition, classification, and prediction research. Furthermore in [25], the authors suggested the use of grey relational analysis (GRA) to recognize multi-channel surface electromyography (SEMG) utilizing a portable hand motion classifier (HMC). SEMG offered details on the flexion and extension of the fingers, wrist, forearm, and arm. An electrode configuration system (ECS) and GRA-based classifier were used to create a portable HMC that can recognize hand motion from SEMG data. To collect the multi-channel SEMG signals of the respective muscle groups, the ECS comprised seven active electrodes placed around the forearm. Every electrode channel yields six parameters, and by multiplying these six parameters by seven channels, 42 different parameters could be built to create different patterns. To identify 11 hand gestures, these patterns were sequentially given to the GRA-based classifier. This study involved twelve participants, eight of whom were men and four of whom were women. GRA showed the processing speed, computational effectiveness, and correct recognition for identifying SEMG signals when contrasted to the multi-layer neural networks (MLNNs) based classifier. Also, in [26], introduced a hierarchical view pooling network (HVPN) framework for multiscreen deep learning that enhanced multichannel sEMG-based gesture detection by learning both view-specific and view-shared deep features from hierarchically pooled multiview feature spaces. In order to thoroughly assess our suggested HVPN framework, extensive intrasubject and inter subject assessments were carried out using the large-scale noninvasive adaptable prosthetics (NinaPro) dataset. Results demonstrated that the proposed HVPN framework could achieve intrasubject gesture recognition accuracy of 88.4%, 85.8%, 68.2%, and 63.8% when utilizing 200 ms sliding windows to segment data. On the initial five sub databases of NinaPro, the intersubject gesture precision was 84.9%, 82.0%, 65.6%, 70.2%, and 88.9%, outperforming the state-of-the-art techniques by 72.9%, 90.3%, and 84.9%, correspondingly.

In order to manage a prosthetic hand dexterously and identify different finger movements from surface electromyogram (EMG) signals, the authors in [27] aimed to identify an efficient pattern recognition technology with the fewest time domain characteristics. This research had taken into account combined finger activity for 15 individuals and eight channels of EMG from eight healthy subjects. In this research, an attempt was made to identify several categories with the fewest possible attributes. As a result, dual-tree complex wavelet transform was used to pre-process EMG signals in order to increase the discriminating power of the characteristics. Time domain features such as zero crossing, slope sign change, mean absolute value, and waveform length were therefore recovered from the pre-processed data. Different classifiers, including linear discriminate analysis (LDA), NB, quadratic SVM, and cubic SVM with and without feature selection algorithms, were used to examine the effectiveness of retrieved features. To determine the impact of features, the feature selection was already investigated utilizing particle swarm optimization (PSO) and ant colony optimization (ACO) with various numbers of features. The findings showed that, for a significance level of 0.05, a naive Bayes classifier with ant colony optimization performed significantly better than an SVM classifier with selecting features, with an average classification accuracy of 88.89% and a response time of 0.058025 ms, when recognizing 15 different finger movements with 16 features. In [28], researchers suggested a feature model design and optimization approach based on multi-channel EMG signal amplification units to increase the identification rate of multi-modal EMG signals. Furthermore, the acquisition window and recognition rate were trained using the CNN and LSTM (CNN+LSTM) deep learning model. To address the issue of multi-modal surface EMG signal detection, build a feature model using the existing time series surface EMG image. The experimental findings demonstrated that the EMG signal processed using the Fast Fourier Transform (FFT) as the characteristic value performed better under the same network structure. In [29], the authors offered an electromyographic signal-based model for hand gesture identification. The model replies with a recognition accuracy of 90.7% in about 29.38 milliseconds (real-time). The main window and a sub-window were used in a sliding window technique. A portion of the signal visible through the main window was observed through the sub-window. Data collection, preprocessing, feature extraction, classification, and postprocessing were the five building pieces that make up the model. They analyzed the electromyographic signals utilizing Myo Armband for data collecting. Authors correct, filter, and identify the muscle movement for preprocessing. The authors created a feature vector for feature extraction utilizing the preprocessed signal values and the outcomes of a variety of functions. They employed a feed forward neural network to label each sub-window observation for categorization. Furthermore, to identify the main window observation during post-processing, they used the simple majority voting method.

In [30], described a novel approach to surface electromyography-based individual finger movement prediction (EMG). A multifunctional prosthetic hand device was meant to be controlled deftly in real-time by using this way. 16 single-ended channels were placed on the forearms of healthy volunteers to record the EMG data. The subjects followed the visual instructions to execute a series of finger movements in time with the EMG recording. The stages in our method were as follows: authors retrieve the mean average value (MAV) of the EMG to be utilized as the feature for classification; authors piecewise linear model the dynamics of the EMG feature; authors implemented hierarchical hidden Markov models (HHMM) to capture transitions between linear models, and authors finally implement Bayesian inference as the classifier. In comparison to popular real-time classifiers, the classifier's performance was compared. The findings demonstrated that the current method configuration classifies EMG data comparable to the top evaluated classifiers while requiring computing complexity that was equivalent to or less. Similarly, the authors in [31], the authors suggested a fresh approach for real-time hand gesture identification. This model's input was surface electromyography, which was determined by the forearm-mounted Myo armband's commercial sensor. The user's most recent gesture that was executed was labeled as the output. K-Nearest Neighbor and dynamic temporal warping techniques provided the foundation of the suggested model. The model was capable of learning to identify any hand gesture. They assessed and compared the accurateness in identifying five different classes of gestures to the precision of the Myo armband's proprietary system in order to assess how well it performed. This evaluation led to the conclusion that the model outperformed the Myo system (83% accurate, compared to 86% for the method). Moreover in [32], the authors examined the effectiveness of machine learning techniques for recognizing gestures when they were applied to data from surface double-channel electromyography. Eight different kinds of palm movements were identified by comparative study. The analysis's findings supported the idea that, in order to improve recognition precision and expanded the range of gestures taken into account, the placement of the muscle groups must be taken into account. Furthermore in [33], an sEMG-based real-time recognition of hand gestures model was proposed. They captured sEMG signals with an armband and segmented the data for feature extraction using a sliding window technique. The training dataset was used to create and train an Feed Forward artificial neural network (ANN). The gesture could be recognized using a test technique when the ANN classifier's threshold of activation times for recognized label times was met. They employed a set of five gestures from every person in the experiment and real sEMG data from twelve subjects to assess the model. The average recognition rate was 98.7%, and the average response time was just 227.76 ms, or around one-third of the gesture time. As a result, the pattern recognition system could be capable of recognizing a gesture even before it was fully executed.

Furthermore, to increase the rate of accuracy in the prediction of hand movements, a novel deep learning-based method was developed by authors in [34]. To begin with, 4-channel surface EMG (sEMG) signals were recorded from 30 participants whilst they simulated 7 various hand gestures: Ulnar Deviation, Radial Deviation, Punch, Open Hand, Radial Flexion, and Extension. Every movement was discovered in a different part of the acquired sEMG signals. ShortTime Fourier Transform was then used to construct spectrogram pictures of the segmented sEMG signals (STFT). The coloured spectrogram images that were produced were trained using a ResNet-based 50-layer Convolutional Neural Network (CNN). The suggested technique resulted in a test accuracy of 99.59% and an F1 Score of 99.57% for seven different categories of hand gestures. In [35], the authors suggested a model for real-time hand gesture identification. This model utilized the surface electromyography (EMG) data collected by the Myo armband on the forearm muscles as input. Through a training process, the suggested model can be trained to recognize every hand gesture from any person. In order to complete this procedure, a user must record their forearm's EMG five times for two seconds each as someone makes the motion to be recognized. The EMGs observed through a window were categorized using the dynamic time warping and k-nearest neighbor methods. They also incorporated a muscular activity detector into the suggested model, which shortens processing time and increases recognition accuracy. They tested the suggested model and found it to be 89.5% accurate at identifying the five movements that the Myo armband's proprietary recognition system defined. Likewise, in [36], In order to control a bionic hand, a prototype system for identifying hand positions was built in this research by analyzing sEMG signals taken at the flexor digitorum superficialis and extensor digitorum muscles. They utilized the k-nearest-neighbors (KNN) method as the classifier to accomplish hand-posture recognition, and they adopted a number of features frequently used in earlier studies, including mean absolute value, zero crossing, slope sign change, and waveform length. An Arduino microprocessor was used to operate the bionic hand. It translated the signals obtained from the classification process and supplied them to the servo motors operating the prosthetic fingers. They developed a two-channel sEMG pattern-recognition system that could recognize human hand positions and direct a homemade bionic hand to mimic such postures. In the online trial, the channel combination was used by the KNN technique to identify four different hand positions with a classification accuracy of 94%.

Table 2: Comparison table for Multi-Channel based HGR systems

References	Work done	Channels Used	Dataset Used	Outcomes
[23]	developed an HRM model through unique hybridization of two parallel routes (one convolutional and one recurrent), coupled via a fully-connected multilayer network	two	NinaPro DB2	suggested HRM and TCNM achieved a remarkable HGR rating of 98.01% and 92%.
[24]	Presented an electromyography (EMG) signal collection model for use in research on human-computer interaction.	Four	BIOPAC MP36 device employing Ag/AgCl surface bipolar electrodes	This data can be used for developing EMG-based hand movement controller systems
[25]	Used GRA and HMC based hand gesture recognition systems	Multiple channels	NA	Proposed model was able to identify 11 different types of hand gestures
[26]	introduced a hierarchical view pooling network (HVPN) framework for multiscreen deep learning for enhancing multichannel sEMG-based gesture detection	Multiple channels	NinaPro	Results demonstrated that the proposed HVPN framework could achieve intrasubject gesture recognition accuracy of 88.4%, 85.8%, 68.2%, and 63.8% when utilizing 200 ms sliding windows to segment data.
[27]	Proposed an efficient pattern recognition based HGR system in whch classification was done by LDA, NB, Quadratic SVM and Cubic SVM with and without Feature Selection algorithms	Eight	NA	naive Bayes classifier with ant colony optimization performed significantly better than an SVM classifier with selecting features, with an average classification accuracy of 88.89% and a response time of 0.058025 ms, when recognizing 15 different finger movements with 16 features
[28]	Proposed an effective HGR system in which CNN and LSTM was used	Multiple channels	NA	Performed better than exiting models with complexity issues.
[29]	Employed Feed Forward NN for detecting and identifying hand gestures	Multiple channels	Myo Armband	Recognition accuracy of 90.7% in about 29.38 milliseconds (real-time).
[30]	implemented hierarchical hidden Markov models (HHMM) to capture transitions between linear models, and authors finally implement Bayesian inference as the classifier	16 channels	Manual DB was created	Classifies EMG signal with better accuracy and reduced complexity
[31]	Proposed KNN and dynamic temporal warping techniques based HGR system	Multiple channels	Myo armband's	Accuracy rate of 83% was attained
[33]	Proposed sliding window and Feed Forward ANN based real time HGR system	Multiple channels	Armband	average recognition rate was 98.7%, and the average response time was just 227.76 ms
[34]	A ShortTime Fourier Transform and CNN based gesture recognition model was developed for identifying 7 gestures	Four channels	Data collected manually from 30 participants	suggested technique resulted in a test accuracy of 99.59% and an F1 Score of 99.57% for seven different categories of hand gestures.
[35]	authors suggested a model for real-time hand gesture identification that was based on dynamic time warping and k-nearest neighbor methods	Multiple channels	Myo armband	Accuracy rate of 89.5%was attained
[36]	Proposed a KNN based HGR system for identifying hand positions	Two	NA	classification accuracy of 94% was attained

However, as we have mentioned in prior sections that by using multiple channels, the complexity of the HGR system increases which in return lower the accuracy rate. From the above literatures, it has been observed that by using 2 channels in the HGR system, not only the complexity issue is resolved but also the reliability and efficiency of the model can be enhanced. Keeping in mind, the importance of using 2 channels in HGR systems, the next subsection of this paper will review some of the recent 2 channels based HGR systems.

Two-channel based HGR systems

The authors in [37] focused on a minimum strategy in which they attempt to categorize four motions using just two EMG channels attached to the flexor and extensor muscles of the forearm. A support vector machine (SVM) was used as a classifier together with a two-channel EMG system, high-dimensional feature space, and other techniques. Additionally, the system's tolerance for rejecting unwanted gestures made during bodily movement was assessed, and two strategies were used to make sure this happened: one depending on an SVM threshold and another one based on the insertion of a locking gesture. As a result, the system was able to identify up to five gestures (hand closing, hand opening, wrist flexion, wrist extension, and double wrist flexion), with a taught user's classification accuracy ranging from 95% to 100% and robustness against various body actions assured by the locking feature. In [38], the authors introduced a case study that evaluated the applicability of a newly developed two-channel myoelectric controller for a prosthetic hand with several fingers. The authors utilized a PCA-based method to control 16-degrees of freedom robotic hand that was underactuated in real-time. In this research study, an able-bodied volunteer participant was chosen to test the device. The forearm EMG signals were used to drive the prosthesis when they were captured by active surface electrodes and properly processed. The trials showed that it was possible to create bio-inspired myoelectric hand prosthesis with a control mechanism that was also simple and human-friendly. It could soon be possible for hand amputees to participate in the validation of the PCA-based EMG controller. The authors in [39] showed a flexure hinged anthropomorphic prosthetic hand that could be moved by surface electromyography (sEMG) impulses from two electrodes. The prosthetic hand comprised a small structure, 5 fingers, and 4 Degrees of Freedom (DoFs), all of which were controlled by 4 separate actuators. Pattern recognition was used, and the best feature set was determined to be Mean Absolute Value (MAV), Variance (VAR), the fourth-order Autoregressive (AR) coefficient, and Sample Entropy (SE), with Linear Discriminant Analysis (LDA) being used to minimize the dimensionality issues. Similarly, in [40], researchers suggested a HGR model by using R2 value determined from a one-way analysis of variance. The authors evaluated features like time-frequency domain features includes time, frequency, time-frequency, and principal component analysis (PCA). The PCA of time-frequency domain EMG features was used in our study to identify six different grab types utilizing signals from two EMG channels. This method had the greatest recognition rate (97.5%). This study demonstrated the importance of the R2 value in feature selection. In [41], authors employed two-channel sensors to attempt to recognize six widely used hand gestures, and they contrasted the classification accuracy and computation times of various methods. Finally, they used a back propagation neural network (BPNN) classifier that balanced accuracy and computation time to reach a recognition accuracy of 91.93% using three temporal domain features. In [42], In order to recognize double-channel EMG signals, a new method based on sample entropy and PSO-SVM was proposed. This method takes into account the needs for wearable devices, such as being injury-free, comfortable, and light. An adjacent sliding window that doesn't overlap was used to first segment the signal. Furthermore, a feature vector was quickly constructed from the sample entropy of the valid information once each window's signal was decomposed using EMD. Five approaches were then utilized to compare and categorize the five paired finger movements for pinch gestures. According to the experimental findings, the method (IPSO-SVM-WMV) integrated sample entropy had stronger resilience, real-time, and anti-interference ability in double-channel EMGs signal detection, and the accuracy of the classification was greater than PSO-SVM. In [43], In order to recognize static hand gestures inside intricate skin-like background regions in an efficient and clever way, this study suggested a dual-channel convolutional neural network (DCCNN) structure and enhanced centroid watershed algorithm (ICWA)-based integrated hand motion identification model. This method's efficiency resulted from more precise hand motion segmentation from an initial image utilizing the ICWA. The divided picture and the related Local Binary Patterns (LBP) features that were retrieved from the actual picture are then utilized as inputs for two different classification channels of the developed DCCNN. This research made contributions by combining Principal Component Analysis (PCA) for dimension reduction and a convexity detection process to recognize the secant line between the palm and arm, as well as by developing a novel technique for minimizing the image gradient difference while segmenting in the YCrCb color space.

Table 3: Comparison of Two channel based HGR systems

References	Work done	Channels Used	Outcomes
[37]	focused on a minimum strategy in which they used SVM for categorizing four motions using just two EMG channels	Two	classification accuracy of 95% was attained
[39]	Proposed an effective HGR system in which they used LDA for reducing dimensionality and PCA for identifying gestures	Two	Effective identifies various hand gestures
[40]	Proposed an efficient HGR system in which they used R2 value from one way of variance	Two	greatest recognition rate of 97.5%.

[41]	Proposed a BPNN based HGR system for detecting hand gestures	Two	recognition accuracy of 91.93% was attained
[42]	Proposed a new method based on sample entropy and PSO-SVM for detecting 5 types of gestures	Two	Efficient HGR model with highly accurate results
[43]	suggested a dual-channel convolutional neural network (DCCNN) structure and enhanced centroid watershed algorithm (ICWA)-based integrated hand motion identification model.	Two	Efficiently detected various hand gestures

II. Conclusion

In this review paper, we have analyzed and discussed the importance of using optimum number of channels in any Hand Gesture Recognition System. In this regard, we analyzed that usually researchers embed one or multiple channels in their HGR systems. However, after analyzing the literature, we observed that in case of single channels based HGR system huge distortions can occur due to noise which in turn reduces the accuracy of system. Moreover, it becomes difficult for experts to distinguish between SMG signal and noisy signal. Therefore, experts started to use multi channels in their work. However, the problem with using multiple channels is that complexity of the HGR models increases which in return increases the computational time. hence, it is recommended to use ideal number of channels that can lower complexity and extract EMG signals easily. It is observed that two channels based HGR system is showing effective results in terms of accuracy with reduced complexity.

References

[1]. Clough, Sharice, and Melissa C. Duff. "The role of gesture in communication and cognition: Implications for understanding and treating neurogenic communication disorders." Frontiers in Human Neuroscience 14 (2020): 323.

[2]. Naik, Ganesh R., et al. "Subtle hand gesture identification for hci using temporal decorrelation source separation bss of surface emg." 9th Biennial Conference of the Australian Pattern Recognition Society on Digital Image Computing Techniques and Applications (DICTA 2007). IEEE, 2007.

[3]. Weiss, L.D.; Weiss, J.M.; Silver, J.K. Easy EMG E-Book: A Guide to Performing Nerve Conduction Studies and Electromyography; Elsevier Health Sciences: Amsterdam, The Netherlands, 2015.

[4]. Rodriguez-Falces, J.; Navallas, J.; Malanda, A. EMG modeling. In Computational Intelligence in Electromyography Analysis-A Perspective on Current Applications and Future Challenges; InTechOpen: London, UK, 2012

[5]. De Luca, C.J. A model for a motor unit train recorded during constant force isometric contractions. Biol. Cybern. 1975, 19, 159–167.

[6]. K Agamemnon, K Iris, MS Erden, et al., Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements. J. Neuroeng. Rehabil. **14**(1), 71 (2017)

[7]. F Zhao, H Nie, H Chen, Group buying spectrum auction algorithm for fractional frequency reuses cognitive cellular systems. Ad Hoc Netw. **58**, 239–246 (2017)

[8]. Naik, Ganesh R., et al. "Improving Isometric Hand Gesture Identification for HCI based on Independent Component Analysis in Bio-signal Processing." PRIS. 2007.

[9]. S. Raurale, J. McAllister, and J. M. del Rincon, "Emg acquisition and hand pose classification for bionic hands from randomly-placed sensors," in 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), April 2018, pp. 1105–1109.

[10]. Xun Chen and Z Jane Wang, "Pattern recognition of number gestures based on a wireless surface emg system," in Biomedical Signal Processing and Control, 2013, vol. 08, pp. 184–192.

[11]. Takamitsu Matsubara, Jun Morimot, "Bilinear Modeling of EMG Signals to Extract User-Independent Features for Multiuser Myoelectric Interface", IEEE Transactions On Biomedical Engineering, Vol. 60, No. 8, August 2013,pp. 2205-2213.

[12]. Rui Sun, Rong Song, Kai-yu Tong, "Complexity Analysis of EMG Signals for Patients after Stroke During Robot-Aided Rehabilitation Training Using Fuzzy Approximate Entropy", Transactions On Neural Systems And Rehabilitation Engineering, Vol. 22, No. 5, September 2014, pp-1013-1019

[13]. Vijay Pal Singh, Dinesh K. Kumar, "Classification of low level figure contraction from single channel surface EMG", 30th Annual International IEEE EMBS Conference, Canada, August 2008, pp. 2900-2903.

[14]. Aaron J. Young, Lauren H. Smith, Elliott J. Rouse, Levi J. Hargrove, "Classification of Simultaneous Movements Using Surface EMG Pattern Recognition", IEEE Transactions on Biomedical Engineering, Vol. 60, No. 5, pp. 1250-1258, May 2013

[15]. Tavakoli, Mahmoud, Carlo Benussi, and Joao Luis Lourenco. "Single channel surface EMG control of advanced prosthetic hands: A simple, low cost and efficient approach." Expert Systems with Applications 79 (2017): 322-332.

[16]. Mane, S. M., et al. "Hand motion recognition from single channel surface EMG using wavelet & artificial neural network." Procedia Computer Science 49 (2015): 58-65.

[17]. A. K. Das, V. Laxmi and S. Kumar, "Hand Gesture Recognition and Classification Technique in Real-Time," 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN), 2019, pp. 1-5, doi: 10.1109/ViTECoN.2019.8899619.

[18]. Cao, Junyi, Zhongming Tian, and Zhengtao Wang. "Hand gestures recognition based on one-channel surface EMG signal." Journal of Software Engineering and Applications 12.9 (2019): 383-392.

[19]. Wu, Y., Liang, S., Zhang, L. et al. Gesture recognition method based on a single-channel sEMG envelope signal. J Wireless Com Network **2018**, 35 (2018).

[20]. R. Sheng and Z. Zhang, "A hand gesture recognition using single-channel electrodes based on artificial neural network," 2019 IEEE 8th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), 2019, pp. 209-213, doi: 10.1109/ITAIC.2019.8785724.

[21]. Yina, Guo, and Zhou Dawei. "Single channel surface electromyography blind recognition model based on watermarking." Journal of Vibration and Control 18.1 (2012): 42-47.

[22]. He, Jiayuan, et al. "Wrist and finger gesture recognition with single-element ultrasound signals: A comparison with single-channel surface electromyogram." IEEE Transactions on Biomedical Engineering 66.5 (2018): 1277-1284.

[23]. Rahimian, Elahe, et al. "Surface EMG-based hand gesture recognition via hybrid and dilated deep neural network architectures for neurorobotic prostheses." Journal of Medical Robotics Research 5.01n02 (2020): 2041001.

[24]. Ozdemir, Mehmet Akif, et al. "Dataset for multi-channel surface electromyography (sEMG) signals of hand gestures." Data in brief 41 (2022): 107921.

[25]. Du, Yi-Chun, et al. "Portable hand motion classifier for multi-channel surface electromyography recognition using grey relational analysis." Expert Systems with Applications 37.6 (2010): 4283-4291.

[26]. Wentao Wei, Hong Hong, Xiaoli Wu, "A Hierarchical View Pooling Network for Multichannel Surface Electromyography-Based Gesture Recognition", Computational Intelligence and Neuroscience, vol. 2021, Article ID 6591035, 13 pages, 2021. https://doi.org/10.1155/2021/6591035

[27]. Purushothaman, G., Vikas, R. Identification of a feature selection based pattern recognition scheme for finger movement recognition from multichannel EMG signals. Australas Phys Eng Sci Med 41, 549–559 (2018). https://doi.org/10.1007/s13246-018-0646-7

[28]. D. Bai, T. Liu, X. Han, G. Chen, Y. Jiang and Y. Hiroshi, "Multi-Channel sEMG Signal Gesture Recognition Based on Improved CNN-LSTM Hybrid Models," 2021 IEEE International Conference on Intelligence and Safety for Robotics (ISR), 2021, pp. 111-116, doi: 10.1109/ISR50024.2021.9419532.

[29]. Motoche, C., Benalcázar, M.E. (2018). Real-Time Hand Gesture Recognition Based on Electromyographic Signals and Artificial Neural Networks. In: Kůrková, V., Manolopoulos, Y., Hammer, B., Iliadis, L., Maglogiannis, I. (eds) Artificial Neural Networks and Machine Learning – ICANN 2018. ICANN 2018. Lecture Notes in Computer Science(), vol 11139. Springer, Cham. https://doi.org/10.1007/978-3-030-01418-6_35

[30]. N. Malešević, D. Marković, G. Kanitz, M. Controzzi, C. Cipriani and C. Antfolk, "Decoding of individual finger movements from surface EMG signals using vector autoregressive hierarchical hidden Markov models (VARHHMM)," 2017 International Conference on Rehabilitation Robotics (ICORR), 2017, pp. 1518-1523, doi: 10.1109/ICORR.2017.8009463.

[31]. M. E. Benalcázar, A. G. Jaramillo, Jonathan, A. Zea, A. Páez and V. H. Andaluz, "Hand gesture recognition using machine learning and the Myo armband," 2017 25th European Signal Processing Conference (EUSIPCO), 2017, pp. 1040-1044, doi: 10.23919/EUSIPCO.2017.8081366.

[32]. Ponomarchuk, Y. V., and I. V. Kuznetsov. "Comparative Analysis of Efficiency of the Machine Learning Methods for Gesture Recognition Using Double-Channel Electromyography." Journal of Physics: Conference Series. Vol. 2134. No. 1. IOP Publishing, 2021.

[33]. Zhang, Zhen, et al. "Real-time surface EMG pattern recognition for hand gestures based on an artificial neural network." Sensors 19.14 (2019): 3170.

[34]. Ozdemir, Mehmet Akif, et al. "EMG based hand gesture recognition using deep learning." 2020 Medical Technologies Congress (TIPTEKNO). IEEE, 2020.

[35]. M. E. Benalcázar et al., "Real-time hand gesture recognition using the Myo armband and muscle activity detection," 2017 IEEE Second Ecuador Technical Chapters Meeting (ETCM), 2017, pp. 1-6, doi: 10.1109/ETCM.2017.8247458.

[36]. Shi, Wan-Ting, et al. "A bionic hand controlled by hand gesture recognition based on surface EMG signals: A preliminary study." Biocybernetics and Biomedical Engineering 38.1 (2018): 126-135.

[37]. Tavakoli, Mahmoud, et al. "Robust hand gesture recognition with a double channel surface EMG wearable armband and SVM classifier." Biomedical Signal Processing and Control 46 (2018): 121-130.

[38]. G. Matrone, C. Cipriani, M. C. Carrozza and G. Magenes, "Two-channel real-time EMG control of a dexterous hand prosthesis," 2011 5th International IEEE/EMBS Conference on Neural Engineering, 2011, pp. 554-557, doi: 10.1109/NER.2011.5910608.

[39]. Wang, Nianfeng, Kunyi Lao, and Xianmin Zhang. "Design and myoelectric control of an anthropomorphic prosthetic hand." Journal of Bionic Engineering 14.1 (2017): 47-59.

[40]. Kakoty, N.M., Hazarika, S.M. & Gan, J.Q. EMG Feature Set Selection Through Linear Relationship for Grasp Recognition. J. Med. Biol. Eng. **36**, 883–890 (2016).

[41]. Y. Yang et al., "A Multi-Gestures Recognition System Based on Less sEMG Sensors," 2019 IEEE 4th International Conference on Advanced Robotics and Mechatronics (ICARM), 2019, pp. 105-110, doi: 10.1109/ICARM.2019.8834153.

[42]. Zhang, He, and Mengwei Su. "Hand gesture recognition of double-channel EMG signals based on sample entropy and PSO-SVM." Journal of Physics: Conference Series. Vol. 1631. No. 1. IOP Publishing, 2020.

[43]. X. Dong et al., "A Static Hand Gesture Recognition Model based on the Improved Centroid Watershed Algorithm and a Dual-Channel CNN," 2018 24th International Conference on Automation and Computing (ICAC), 2018, pp. 1-6