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An Innovative Human-Computer Interaction (HCI) for Surface Electromyography (EMG) Gesture Recognition

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Abstract: The interface between citizens and elegant cities is human computer interaction (HCI), a place that is crucial in bridging the application gap for information technology in contemporary cities. Hand gestures (HG) are generally recognized as a potential HCI technique, and the use of Surface Electromyograms (SEMG) to recognize Human Hand Gestures (HHG) is a significant area of study. Modern signal processing techniques, instead, are not robust in feature extraction utilizing Principal Component Analysis (PCA), using feature re-extraction, and guide respect with SEMG signals; there be motionless several technical issues that need to be resolved. The way for instance, can myoelectric control be kept available in intermittent use, as time variability has a significant negative impact on pattern recognition quality yet is unavoidable in regular use. Developing a solid HCI also requires ensuring the myoelectric control system's efficacy and dependability. In this study, Augmented Partial Swarm Optimization and Modified K-Nearest Neighbor (APSO-MKNN) are used in the HGR system that can eliminate redundant information in SEMG signals and increase the effectiveness and precision of recognition. The investigational findings help lower the time differences in Gesture Recognition (GR) based on SEMG.This study is focused on optimizing the time differences in SEMG pattern recognition. The identification approach that is proposed in this study has the possibility of increasing the long-term accuracy of the generalization of an HCI system. Additionally, the proposed framework can simplify the process of data collecting prior to having a gadget prepared and ready for usage.

***Keywords**: hand gestures (HG), human-computer interaction (HCI), principal component analysis (PCA), surface electromyogram (SEMG), augmented partial swarm optimization, and modified k-nearest neighbor (APSO-MKNN)*

1. Introduction

As computer power has increased, more computing gadgets are now a part of everyday life for people. So that people may engage with them, a wide range of apps and interfaces were created. While these systems function more naturally, interacting with them is simpler. A key component of HCI, that examines computer knowledge made to understand orders issued by people, is hand gesture recognition (HGR). HGR models are HCI to ascertain the gesture being made alongside the time it was made [1]. Technology now allows for a variety of ways for people to communicate with computer-based systems. Aspects of expressiveness including temporal, visual, structural, and emotional ones are all covered in close collaboration by voice, facial, and hand or body movements. One of the key methods in HCI is the recognition of Hand Gestures (HG). Recognition of HG has a broad variety of uses, including teleoperation, entertainment, and medicine. HG includes the corresponding flexion of the user's hands and contains data that are often too ethereal for a computer to understand straightforwardly. Enhancing quality of living is a significant use of HG recognition [2].

Humans are attempting to speak with computers more organically these days due to the fast advancement of information technology. There is no longer a natural method to engage, and traditional HCI input devices like the mouse, keyboards, and remotes lack versatility. Generally speaking, vocal instructions and gestures are natural methods for individuals to interact with a computer. The most crucial way that computer vision is used in autonomous structures is in HCI. To facilitate effective HCI, accurate data must be collected on form, behavior, and motion. These human targets may be correctly identified and recognized by an efficient characteristic analysis. Before HCI, the identification of the target and the environment both play a key role and present several obstacles [3]. One of the simplest and

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most profound kinds of human communication is HG. Consequently, HG recognition in HCI has drawn more interest in a variety of applications, including augmented reality, robot manipulation, rehabilitation training, and sign language identification. Beyond the well-discussed hand gesture detection algorithms enabled by computer vision, SEMG data, that indicate the overlaid electric activity of muscle fibers, also have a lot of promise. SEMG signals are commonly used as control signals for robotic control, especially in the area of medical robotics that improves the intuitive interface between human and surgical robots. Over the last several decades, several SEMG signals-based hand identification techniques have been presented [4].

One of the most crucial life skills that people have is the capacity to communicate. A proportionate increase in HCI has resulted from the quick development of digital gadgets. HCI systems can only accept user input via conventional means such as a keyboard, mouse, or touchscreen. As a result, the need for alternative HCI input modes to replace these extra devices is developing. Free space writing's inherent flexibility gives users a simple way to enter data into HCI applications [5]. The development of HCI based on gestures, vision, and speech has received a lot of attention. Recognition of HG offers an intelligent, comfortable, and natural HCI method. To make it simpler for deaf individuals to interact with society, sign language recognition aims to automatically translate signs using computers. It offers a strong framework for the development of globally applicable gesture-based HCI and is fairly structured, using an alphabet and symbols. The electrical manifestation of neuromuscular activity linked to a contracting muscle is known as a SEMG. Physically disabled people may control assistive technology and rehabilitation with the use of this technology. SEMG is also used in a variety of scientific disciplines, including biology, gesture-based controlling applications, neuron physiology, recognizing signs, military-related games, and virtual reality [6]. The electrical nature of human nerves may be used to connect human neural networks to machines. The use of SEMG may enable this difficult coupling. The creation and use of this SEMG -based control have significantly improved the quality of life for elderly and handicapped persons by increasing their social acceptability in our society [7]. The ability to create an HCI that allows for a universal, natural, and user-friendly connection with computers may still be maintained by wearable technology. With the introduction of wearables, there is a chance to do away with a physical controller and communicate directly with the computer. The skin surface just above the muscle being measured with the SEMG captures muscle activity. Utilizing surface electrodes, the signal is captured [8]. Recognition of HG offers an intelligent, comfortable, and practical HCI method. Even though the majority of modern technologies employ sensors and picture-recording devices, several issues have arisen due to the shifting light and the color or pattern of the backdrop. Another two possible technologies for gesture sensing are accelerometers and SEMG sensors. A biological signal called an SEMG tracks electrical currents produced during muscle contractions and is a representation of neuromuscular processes. SEMG signals try to display the activity of the muscles while making a gesture, while accelerometers read the acceleration from vibrations and gravity [9]. Virtual reality, that simulates certain real-world scenarios to provide viewers with an immersive experience, is often utilized in industries such as education, healthcare, the military, industrial production, and others. Users need to be given different sensory cues to imitate real-world settings for virtual reality to be realized. The virtual reality system must simultaneously gather the user's position data, real-time action data, physiological signals, and command data. The development of virtual reality thus places a lot of emphasis on the design of different sorts of HCI devices [10]. The HGR system uses Augmented Partial Swarm Optimization and Modified K-Nearest Neighbor (APSO-MKNN) to analyze the GR problem. This technique may enhance the effectiveness and precision of identification while simultaneously deleting extraneous data from SEMG signals.

Research [11] provided an extensive and methodical assessment of the viability of HG identification utilizing SEMG signals captured at the wrist because customers are more accustomed to wrist-worn devices. Both wrist and forearm signals are simultaneously recorded, and the signals and information quality are directly compared. The study [12] compared multiday surfaces SEMG recordings and assesses that myoelectric organization has been improved using convolutional neural networks (CNNs). It is shown that the recommended CNN has better accuracy at a lower computational cost compared to the previously trained transfer learning (TL) models. The results show that CNN can extract a significant amount of information from SEMG data and can significantly improve pattern identification in myoelectric control systems. SEMG is primarily utilized for HCI, assisted physical rehabilitation, and neuromuscular diagnostics.

Research [13] presented the Sensor-Wise approach that, owing to its great compatibility with the nature of SEMG signals and the structure of convolutional networks, has a stronger capacity to extract features than the SEMG picture method. The method is an excellent choice for hardware implementation because of its high accuracy and slim structure. The SEMG signal is crucial for a variety of applications, including those involving human-computer interfaces, medical diagnostics, and devices for rehabilitation. Myoelectric control is the term used to describe all of these uses. Myoelectric control has been the subject of many studies, although difficulties have emerged. The impact of limb position on SEMG-based gesture identification is one challenge. Even when the gesture is the same, several articles suggest that as the limb postures vary the accuracy of gesture categorization declines. Using five distinct HG, a CNN-LSTM network neural network model is suggested in the present work to allow the identification of dynamic HG [14].

The study [15] introduced the idea of the SEMG graph that opens up new possibilities for the study of SEMG-based tasks beyond gesture detection and replaces the picture and vector sequence representation of SEMG data used in earlier publications. The classification of five typical dynamic movements using a CNN with long short-term memory (CNN-LSTM) is suggested in the present study. Additionally, each dynamic motion would be executed with five distinct limb postures. A developed neural network algorithm with good recognition results is then used by an individual to control the robotic arm [16]. The paper [17] suggested a method for doing real-time gesture identification using a variety of machine-learning techniques that may be used for a wide range of HCI. They use SEMG recordings that continuously sent data to the microcontroller from hand muscles. From the microcontroller, they will gather data that we will subsequently store on an offline server. Investigate the CNN topologies to get an optimum design that can efficiently identify the signals' hidden properties. The results demonstrate that the proposed CNN framework in the study possesses excellent accuracy in classification for SEMG-based HG identification and that the different topologies have a significant influence on CNN performance [18]. The research [19] described the creation of a revolutionary HG recognition system that integrated a wearable armband and a smart glove built of programmable pressure sensor arrays to detect consecutive hand movements to provide new methods. a deep learning approach By training and evaluating the LSTM algorithm using the IMU (Inertial Measurement Unit), SEMG, finger, and palm pressure data acquired, an efficient model for classifying hand motions was created. A performance-based view creation technique is suggested in the first section to choose the best discriminative views from traditional feature sets for SEMG-based gesture detection [20].

2. Methodology

The dataset for the investigation is first gathered in this phase. The dataset includes several samples with a variety of properties or features. Use the Principal Component Analysis (PCA) approach to extract features after obtaining the dataset. The original characteristics of the dataset are converted via PCA into a new collection of uncorrelated variables called principal components, assisting in reducing the dataset's dimensionality. Using the suggested technique known as Augmented Partial Swarm Optimization - Modified K Nearest Neighbor (APSO-MKNN), then continue with feature re-extraction. To improve the classification performance of the dataset, this innovative method combines the strength of swarm optimization with a modified KNN algorithm. Through the use of a swarm of particles' collective intelligence, APSO-MKNN improves the feature subset selection procedure (Fig.1).

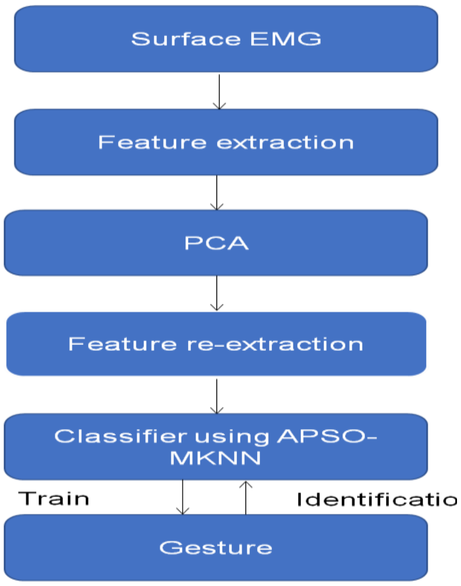

Fig.1. Gesture recognition method

A. Dataset

To perform an HCI, many SEMG-based datasets have been released. The data sets can be used as input by AI systems. The criteria that affect the amount of data are inconsistent, even with the assortment of data in the literature. The ideal combination of sensors, subjects, and gestures should be used to train the AI model to provide a successful HCI. As a gauge of practicality, one may compare the trained model's performance while evaluating the data of additional participants. For these explanations, that continues to be a need for fresh, well-prepared, and precise SEMG -based datasets of HG.

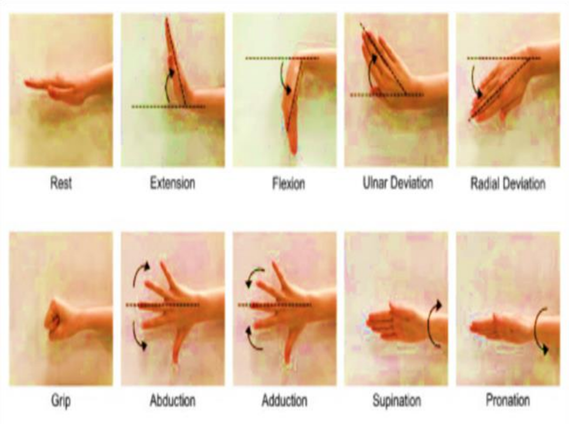

Fig.2. Dataset [21]

A fresh surface with the right amount of channels, individuals, and motions was used to construct the SEMG dataset. The most frequent wrist and HG in everyday life are included in this dataset. The ten often used HG are shown in Fig. 2 as the neutral or resting position, the wrist extended, the wrist flexed, the wrist deviated in one or more directions, the grasped object and the fingers extended, and the wrists pronated or supinated.

B. Feature extraction using Principal Component Analysis (PCA)

Templates matching, a key recognition approach compares a template to be recognized with one that has previously been stored. For feature extraction and matching, the strategy uses the PCA technique. By using PCA, it is possible to minimize the image's dimensionality while retaining a large amount of data. It operates by transforming a collection of correlated variables into a class of linearly uncorrelated variables known as principal components. The major components of the coefficient matrix are calculated using the Eigen Vectors (EV) that were generated from a group of hand images. The first component of these primary components, that are perpendicular to one another and point in the direction with the highest variance, is also the first.

The PCA methodology consists of two stages: training and testing. HG training pictures are used to create the Eigen Space (ES) and map these images to the ES during the training phase. The testing step involves mapping the test image to the same ES and classifying it using a distance classifier.

Algorithm for PCA:

1) Training stage:

a) Calculation of Eigenvectors:

- Acquire the database contain N training images of dimensions $:N \times N: J_1, J_2, J_3 \dots \dots .., .J_M$
- Convert these M images into vectors $Y_j, 1 \leq j \leq M$ of dimension N^2
- Obtain mean image vector Ψ

$$\Psi = \frac{1}{M} \sum_{j=1}^{M} Y_j$$

- Acquire the training image and the mean image vector to create the different images.

$$\phi_j = Y_j - \Psi$$

- Acquire the covariance matrix C having dimensions $N^2 \times N^2$.

$$C\frac{1}{M}\sum_{m=1}^{M}\phi_m\phi_m^{\ T} = AA^S$$

- Acquire EV W_j of $B^S\,B$ [dimensions $M \times M$.

  BB^S has N^2 EV and Eigenvalues.

  $B^S\,B$ has M EV and Eigenvalues.

- Acquire the best M EV of BB^S

$$x_j = Bw_j$$

- Take only X EV corresponding to X largest Eigenvalues.

2) Training database representation using EV:

- The weight of each training image is calculated as:

$$u_i = x_i^S.\left(Y_j - \Psi\right), where\ i = 1,2,3,\dots\dots M$$

- Weight Vector (WV) is determined as:

$$\mu = \left[u_{1,}u_2, u_{3,\dots\dots\dots,}u_m\right]^S;$$

3) Testing Stage:

Allow the weight of the image to be determined $\left(u_{j,}\right)$ is calculated by multiplying Eigenvector $u_{j,}$ with the difference image.

$$u_j = x_j^S.(q_{\prime} - \Psi)$$

- WV of an unidentified image is determined as:

$$\mu = \left[u_{1,}u_2, u_{3,\dots\dots\dots,}u_m\right]^S;$$

So, q is recognized as j^{th} HG from the training database.

C. Feature re- extraction

The high-dimensional feature spaces that involve the directly extracted features, Root Mean Square (RMS), Wave- Form Length (WL), and Median Amplitude Spectrum (MAS), are stored making them unsuitable for classification. Enhancing GR accuracy and generalization of the classifier depends on reducing the size of the feature space.

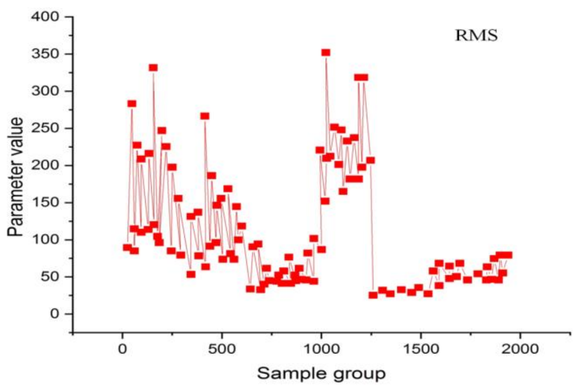

Fig.3. Root Mean Square

The total intensity and kinetics of HG during gestures are captured by the RMS methodology, making it a useful feature extraction method in GR. Intuitive and realistic HCI is made possible by RMS characteristics that are used by GR systems to properly read and categorize user gestures (Fig.3).

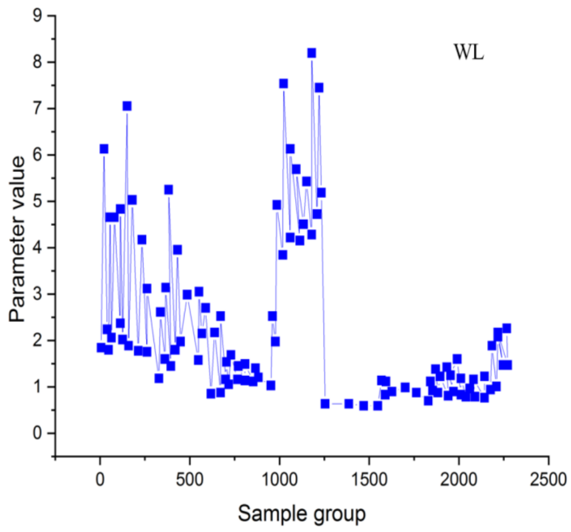

Fig.4. Wave-Form Length

WL uses GR a technology to analyze waveform signals to understand HG. It entails recording and examining the size and length of a waveform created by a user's gesture to identify and categorize certain actions or orders.

The procedure often starts with the collection of sensor data, such as readings from gyroscopes or accelerometers that record the user's hand or body motion. The gesture is represented by waveform signals produced by these sensors (Fig.4).

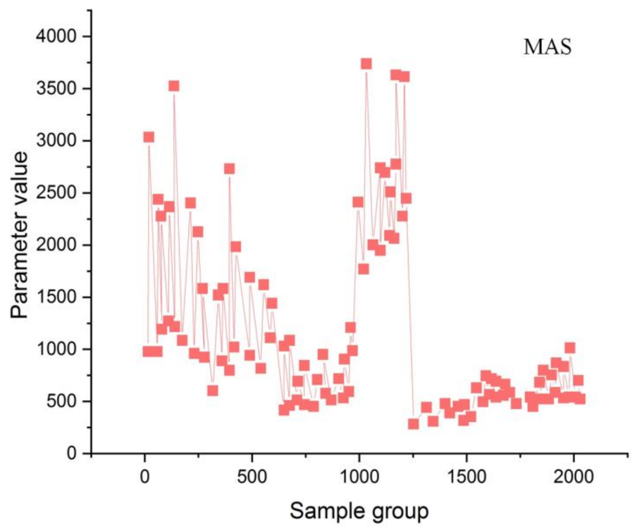

Fig.5. Median Amplitude Spectrum

The frequency content of the signal is essential for recognizing gestures, as it is in HG, MAS analysis is extremely beneficial. It allows precise and effective GR systems that can comprehend and react to HG in a variety of scenarios, such as HCI, virtual reality, and motion-based gaming (Fig. 5).

D. Augmented partial swarm optimization-Modified K-nearest neighbor (APSO-MKNN)

An initialized group of particles in the viable clarification space is created first using the APSO algorithm. Each one of them represents a possible best-case scenario for the intense assessment optimization difficulty, and each particle's attributes can be determined by one of three indicators: posture, motion, and fitness. The individual extreme value and the population's extreme value position are both brought up to date anytime the particle itself is brought up to date. This is done by contrasting the fitness score of the new particle with the efficiency value of the person's extreme value and the overall extreme value. The algorithm's main goal is to update the particle's velocity and location by monitoring the current local optimum solution and the current global optimal solution. The present global optimum solution is the best answer to the issue provided the termination condition is met.

$$X_{jc}^{l+1} = \omega X_{jc}^{l} + d_1 q_1 \left(O_{jd}^{l} - V_{jd}^{l}\right) + d_2 q_2 \left(O_{hd}^{l} - V_{jc}^{l}\right) \quad (1)$$

$$O_{jd}^{l+1} = \left(O_{jd}^{l} - V_{jd}^{l+1}\right) \quad (2)$$

O_{jd}^{l} *and* O_{hd}^{l} represent the optimal positions of the particle of the l^{th} iteration and all the particles in the entire particle swarm, referred to as the particular extremum and the global extremum, respectively. X_{jc}^{l} indicates the d-dimensional element of the velocity vector of the l^{th} iteration particle. V_{jd}^{l} indicates the d-dimensional element of the position vector of the l^{th} iteration particle.

The acceleration constant represented by $d1$ and $d2$, is used to modify the maximum learning step size. The value is taken to be between [0, 2], and take$d1 = d2 = 2$. To improve the unpredictability of the search, $q1$ and $q2$ are two random functions, and in this study, we assume that $q1 = q2 = 1$. The value of, which stands for inertia weight, is typically [0.1, 0.9]. It is used to modify the solution space's search bounds.

Strong global search capabilities are present where ω is big, while strong local search capabilities are present where ω is small. Consequently, the algorithm's ability to achieve convergence will be greatly enhanced if ω decreases linearly with time. These are the iteration formulas:

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min})}{C_{max}} \times C_j \quad (3)$$

The maximum and minimum weighting coefficients are specified in the formula asωmax, *and* ωmin, respectively. Select$\omega max = 0.9, \omega min = 0.4$, and find that the method performs best at these values. The iterations and total iterations are denoted by C_j, *and* C_{max}, respectively.

The most important factors in the MKNN algorithm's implementation are classification rules, K value selection, and distance measurement. The training data set is finished the feature space is split up into several subspaces while the aforementioned criteria are found. Decision rules decide and give each feature area its own identity. The category of the matching subspace is the category of test samples, and it is obtained for each training instance v_j.

There are several methods to measure distance. It has been thoroughly examined in the study's last portion. Manhattan distance and Euclidean distance are the primary distance measures used in this study. The K value that is used in the MKNN algorithm's parameters will have a significant influence on the classification result of the algorithm.

There will be over-fitting events, such as $K = 1$ in extreme circumstances if the K number is too tiny since the algorithm will utilize training samples from smaller regions to make predictions. Only the closest sample is connected to the test scenario. Although the training error is negligibly tiny and almost zero, the training sample often comprises noisy data. The categorization prediction results will be incorrect if the closest sample is noise, and the test error will be quite high.

A phenomenon known as under-fitting results from the algorithm using training data from broader regions when the K value is too high. The class with the most samples in the training data set is the class that performs best in the test case, such as when $K = n$ occurs in severe situations. K is an odd number, and in applications, the smaller K is often used. Find cross-validation techniques often to choose the right K value.

The most popular and reliable classification decision-making approach in the MKNN algorithm is the majority voting method. These studies also use this methodology. The following describes the majority decide procedure: The set $Xk(v)$ is created using the closest K training samples and the test sample v, and the classification loss function is 0-1 loss. The categorization error rate is given by the following formula if the category of the $Xk(v)$ region is v_j. The samples in $Xk(v)$ are mostly governed by the majority voting rule.

$$\frac{1}{k}\sum_{v_j \epsilon X_k(v)} J\{z_j \neq d_i\} = 1 - \frac{1}{k}\sum_{v_v \epsilon X_k(v)} J\{z_j = d_i\} \quad (4)$$

The two processes for hand recognition in this work, utilizing an MKNN classification model, are as follows: K-nearest neighbor classifier model establishment of the cross-validation approach that is broken down into four parts is used to choose the optimal parameter of K value after selecting proximity metric parameters and classification decision criteria. Determine the distance between each training case and the test case. Sort all distances, and then look for the K training samples that are closest. To obtain the results that are most closely matched, the K closest neighbors are combined and rearranged. Using the verification set operation, the error rate corresponding to each K value is recorded, and the K value with the lowest error rate is chosen as the final parameter.

3. Result and Discussion

The data both before and after dimensionality reduction are employed as input for the APSO-MKNN classifier, and the experimental outcomes of the strategies are compared to show the advantages of using this strategy. The data from the first two days are put to use as a training set, and the data from the third day are put to use as a test set. The parameters of the classifier are determined with the help of the training data set, while the classifier's effectiveness is evaluated with the assistance of the test set. To construct the APSO-MKNN feature data model, one must first investigate the APSO-MKNN network model of each layer.

The eigen values of each gesture are randomly divided into two groups, with the first group functioning as the test set and the second serving as the training set. The data collected over the first two days are used to construct the training set, while the data collected over the third day are used to construct the test set. Each motion will obtain 50 different data sets at random, making the total number of times or tests 100. Following the completion of feature extraction, the data dimension is used to establish the number of input neurons. As a consequence, there are d minus one input neuron and 9 output neurons. Fig. 6 presents the findings of the study.

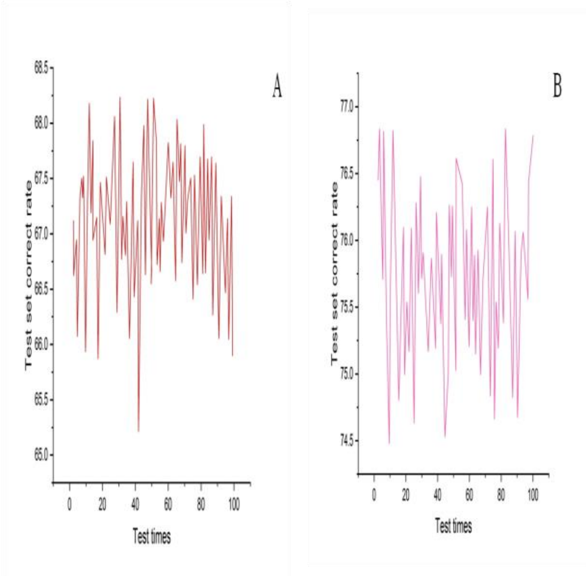

Fig.6. Accuracy of network recognition after PCA dimension reduction

The accuracy of the network often relies on several variables after dimension reduction in network recognition using PCA. By finding the most significant elements that account for the greatest amount of variation in the data, PCA aids in lowering the dimensionality of the input characteristics. The goal of PCA is to maintain the critical information while minimizing computational complexity by removing the less significant components. It usually entails obtaining discriminative features from the input data that are directly pertinent to the job at hand during feature re-extraction for GR. The caliber and discriminative capability of the extracted features determine the extent that gestures are recognized following feature re-extraction.

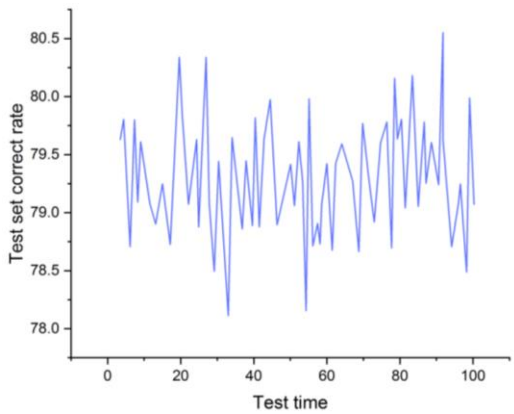

Fig.7. Tests of APSO-MKNN Network Optimized's 100 times accuracy of recognition

As seen in Figure 7, the test samples are similarly chosen at random and run 100 times. Multiple tests may be used to evaluate the performance durability of the APSO-MKNN network that is designed for recognition accuracy. A thorough evaluation of the network's accuracy under different circumstances may be done once 100 tests have been performed. It is possible to apply a variety of optimization methods, including optimization algorithms. By using this approach, the network's performance is increased, perhaps increasing recognition accuracy.

A more accurate evaluation of the APSO-MKNN network's performance after optimization comes from looking at the recognition accuracy throughout 100 tests. It ensures that the network's accuracy is unaffected by chance fluctuations or particular test situations, giving a more accurate picture of the network's capabilities as an entire system.

4. Conclusions

The HCI system for SEMG recognition of HG focuses on analyzing the muscle activity patterns linked to hand motions and converting them into actionable directives or commands for computer systems. Users are now able to manage digital objects, programs, or user interfaces just with HG because of a system that can identify and categorize various HG by monitoring SEMG signals. The dataset includes samples with different traits. After acquiring the dataset, apply PCA to extract features. PCA reduces the dataset's dimensionality by transforming its original characteristics into uncorrelated variables called principal components. Use APSO-MKNN to re-extract features. Swarm optimization and MKNN algorithms improve dataset classification using this method. Using a particle swarm's intelligence, APSO-MKNN improves feature subset selection. Systems for recognizing HG have several drawbacks that may affect the way it operate. Designing a system that is universally accurate in GR is difficult because of the variability in gestures across people that are impacted by things like hand size and shape, skin color, and cultural variances. Low light or harsh shadows might degrade the clarity of the image and make it more difficult to identify gestures accurately. Enhancing real-time speed and latency in HG detection systems is another area for future research. Gesture-based interfaces would become more responsive and natural as a result of faster and more effective algorithms enabling seamless interaction between users and gadgets.

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