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Machine Learning-based sEMG Recognition in Sports Injury Rehabilitation

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Abstract. *Surface Electromyography (sEMG) is widely used in the field of rehabilitation of sports injuries because it contains abundant movement information. The use of sEMG signal pattern recognition classification results to complete rehabilitation actions can save human resources in rehabilitation training. However, the existing sEMG recognition methods are easily disturbed by noise, which makes it tough to extract the feature of sEMG signal, resulting in poor recognition efficiency. Intending to the above issues, this article designs a sEMG recognition method relied on machine learning in sports injury rehabilitation. Firstly, the sEMG is denoised by Variational Mode Decomposition (VMD), and the mode aliasing is reduced by adding alternating direction multiplier iterative algorithm to the signal to be decomposed. Secondly, sEMG characteristics are extracted from time domain, frequency domain and time frequency domain respectively, and then Principal Component Analysis (PCA) is used to diminish the dimension of sEMG characteristics. Finally, the penalty parameters and kernel parameters of the Support Vector Machine (SVM) algorithm are optimized by sample weighting and Particle Swarm Optimization (PSO), and the features after dimensionality reduction are classified and recognized by the optimized SVM algorithm. The experimental outcome indicates that the accuracy, F1 and correlation coefficient R of the designed method are 0.942, 0.951 and 0.985, respectively, which are superior to the comparison method and effectively improve the recognition performance.*
Keywords: sEMG recognition; Variational mode decomposition; Support vector machine; Machine learning; Particle swarm optimization

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1. **Introduction.** At present, Surface Electromyography (sEMG) signal, as a kind of neuroelectric signal, can reflect the contraction state of muscles, which has the features of non-invasive, simple operation, and ahead of limb movement, and is widely used in the field of sports injury rehabilitation [1]. Rehabilitation training for sports injuries is an effective means of restoring athletes' athletic ability, but currently there are problems such as high labor consumption, high work intensity, and low efficiency [2, 3, 4]. Excessive rehabilitation training may lead to muscle fatigue. In rehabilitation training, it is necessary to assess the initial fatigue and deep fatigue state of muscles, and then scientifically set the corresponding exercise load and training volume, and the use of muscle state to accurately identify the movement state during rehabilitation exercises has become a key

issue in the scientific research of rehabilitation training [5, 6]. Recently, the emerging intelligent rehabilitation technology based on sEMG signal can provide an effective means for the objective assessment of the efficacy of sports injury rehabilitation. Therefore, it is of practical value to study the movement recognition technology relied on sEMG signals in sports injury rehabilitation.

1.1. **Related work.** The sEMG requires signal analysis to extract the effective eigenvalues of the muscle information before it can be applied, and the traditional analysis methods are mainly categorized into three kinds: time-domain, frequency-domain, and time-frequency-domain methods. Zhang et al. [7] used the time-frequency domain to classify and recognize six wrist and hand movements of rehabilitated athletes. Li et al. [8] used a new time-domain feature extraction method to classify limb movements in the rehabilitation of sports injuries. Zhou and Fu [9] used an ARMA model to extract features and classify four movements, which achieved a classification effect of 82.7%. Karthick et al. [10] used time and frequency domain methods to construct feature vectors to classify the four movements of the upper limb of an athlete, and achieved good recognition results. Tedesco et al. [11] extracted the muscle features of different gestures by using the power spectral ratio method, and then used a classifier to recognize and classify the muscle features. Jia [12] used wavelet algorithm to extract the features of electromyographic signals, and classified them by using the wavelet algorithm. For the study of EMG signal recognition in sports injury rehabilitation, in addition to feature extraction, how to accurately and efficiently realize action classification is also the key. Margarito et al. [13] denoised the sEMG signals by Empirical Modal Decomposition (EMD) method, then extracted the specific muscle features, and finally classified the actions by using the KNN model. Khairuddin et al. [14] constructed a hand action recognition system by collecting the EMG signals of the above muscles to extract the waveform length features, and then used the KNN model to classify four types of hand actions. Jung et al. [15] used a convolutional neural network based on SEMG to classify and recognize several types of hand movements in human beings. Jumaily [16] proposed a backpropagation neural network based sEMG identification method to extract the features of individual joints relied on the recorded EMG signals and dimensionality reduction of the features using Linear Discriminant Analysis (LDA). Yang et al. [17] proactively used a BP neural network to establish a relationship between the surface EMG signals and the joint angles of the human leg, which can be used to proactively rehabilitate the people with sports injuries. Ahmadi et al. [18] used the K-nearest-neighbor and the decision-tree algorithms to identify 10 hand motions, and the recognition rate was only 81.4%. Meng and Qiao [19] compared the classification performance of the model after removing SVM and GRNN classifiers in different channels, and SVM got the shortest training time and best accuracy after removing three redundant channels. Mohr et al. [20] proposed a new cascade learning model, mainly composed of Generalized Discriminant Analysis (GDA) algorithm and Support Vector Machine (SVM), with an accuracy of 86.54%. Rodrigues et al. [21] proposed a feature-enhanced and improved SVM based on Genetic Algorithm and Linear Negotiator Analysis to categorize 8 gestures, and the accuracy of the recognition reached 89.6%.

1.2. **Contribution.** All of the above research methods have some degree of shortcomings: BP neural network has low accuracy in recognizing sEMG; the training speed is relatively slow due to the repeated iterative learning of the extreme learning machine; KNN has a large amount of computation and a long computation time; the SVM classification idea is simple and has a better classification effect, but the selection of the training parameter values affects the effect of the classifiers. Relied on the above analysis, this article designs a machine learning-based sEMG recognition method in sports injury rehabilitation. Firstly, the Variational Modal Decomposition (VMD) is utilized to incorporate the alternating direction multiplier (ADMM) in the signal to be decomposed to mitigate the modal aliasing and to remove a certain amount of Gaussian white noise. Secondly, to analyze the sEMG signals comprehensively, the time-domain characteristics, frequency-domain characteristics, and time-frequency-domain characteristics in the sEMG are excerpted respectively. Then the extracted 36-dimensional feature vectors are downscaled using Principal Component Analysis (PCA), and finally the relevant parameters of SVM are optimized using sample weighting and Particle Swarm Optimization (PSO), and the optimized SVM is used to classify and identify the downscaled sEMG features.

2. Theoretical analysis.

2.1. Mechanism of sEMG. sEMG is a bioelectrical phenomenon that occurs in muscle tissue when the human body performs a certain action. When a person is moving, the action potential difference can be detected by the signal acquisition electrodes to form EMG signals [22]. Although sEMG is very weak and there is great interference in the acquisition process, it contains rich information and can reflect the state of muscles to a large extent, and still has certain regularity and universality [23].

(1) Weakness. The sEMG is very weak, with amplitudes on the order of µV to mV, probably in the range of 0 to 5 mV.

(2) Alternating current. The sEMG is an alternating current signal, and the magnitude of the signal is affected by changes in the contraction force of the human muscle; the amplitude of the sEMG increases as the muscle contraction force increases.

(3) Symmetry. The sEMG is a symmetrical electrical signal. sEMG is generated by the superposition of multiple sinusoidal signals, and if the arithmetic mean of the sEMG data is calculated, the sum of the positive and negative phase values of the signal always tends to zero.

(4) Low Frequency. The sEMG is a low frequency signal. Under normal conditions, the frequency of the sEMG signal does not exceed 1000 Hz.

2.2. Support vector machine. SVM is a relatively good machine learning algorithm for learning classification functions in pattern recognition tasks, which can solve the problem of nonlinear and unknown systems, learns from data without distribution and without overfitting, and has some robustness to noise [24].

Suppose x is the characteristic vector of the instance, y is the label of the instance, label 1 denotes a positive instance, label -1 denotes a negative instance, and the hyperplane is denoted as $V^T x + a = 0$, where V and a are vectors. The hyperplane is implied in Figure 1. All lines in the region within the two dashed lines can be used as hyperplanes, with positive samples above the region, $y = 1$, and negative samples below the region, $y = -1$. When V and a are determined, the classification function is denoted as $f(x) = V^T x + a$.

The green line in Figure 1 represents the optimal hyperplane, which is unique. The two closest points above and below it is the support vectors, and the geometric interval D between the two support vectors is maximized. For the sample point (x_i, y_i), its geometric interval is as follows.

$$d_i = y_i \left(\frac{V^T}{\|V^T\|} x_i + \frac{a}{\|V^T\|} \right) \tag{1}$$

Then the smallest d value among all sample points is the distance from the support vector to the hyperplane, expressed as follows.

$$d = \min_{i=1,\ldots,N} d_i \tag{2}$$

This translates into an optimization problem under constraints.

$$\begin{cases} \max_{i=1,\ldots,N} d \\ y_i \left(\frac{V^T}{\|V^T\|} x_i + \frac{a}{\|V^T\|} \right) \geq d, \quad i = 1, \ldots, N \end{cases} \tag{3}$$

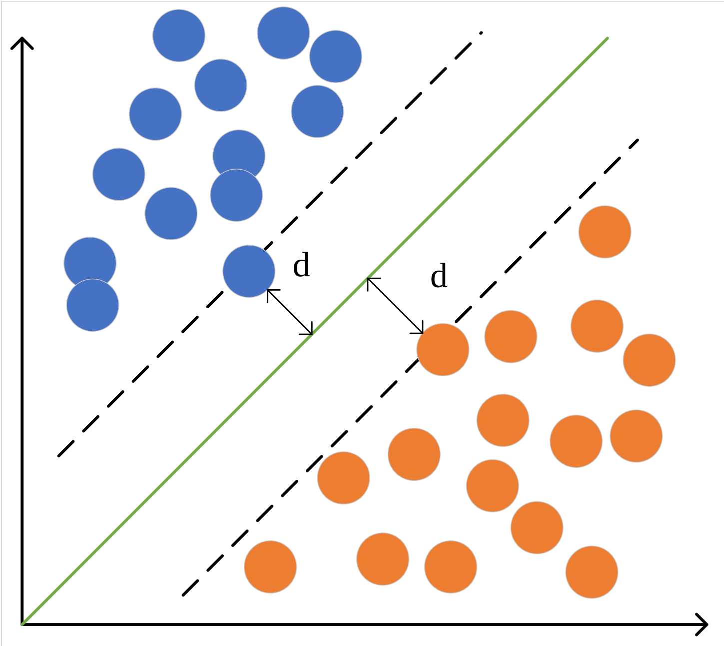

Figure 1. Segmented hyperplane

3. **sEMG variational modal decomposition denoising.** Modal aliasing exists in the traditional denoising of sEMG using EMD [25], and VMD mitigates modal aliasing by incorporating an ADMM iterative algorithm [26] into the signal to be decomposed but removes a certain amount of Gaussian white noise, which improves the subsequent classification and recognition by overcoming the difference in the distribution of athlete-related and athlete-independent EMG data Performance.

To construct a sEMG that is easier to recognize, a VMD is performed for each channel of the sEMG. According to the given number of modal decompositions, the middle frequency and bandwidth of all ingredients are decided through an iterative optimization process, which achieves the frequency field segmentation of the signal and the efficient separation of all modal components (IMF), and reduces the complexity and nonlinearity of the sEMG.

Let the initial sEMG signal $f(t)$ be disintegrated into L finite-bandwidth modal ingredients with different center frequencies, and the constraint is that the superposition of each modal component is equivalent to that of the initial signal. The constrained variational equation is as bellow.

$$\min_{\{u_l\},\{\omega_l\}} \left\{ \sum_l \left\| \partial_t \left[(\delta(t) + j/\pi t)^* u_l(t) \right] e^{-j\omega_l t} \right\|_2^2 \right\} \tag{4}$$

where $\sum_{l=1}^{L} u_l = s$, $\{u_l\}$, $\{w_l\}$ are the L-th modal ingredient and its middle frequency after modal decomposition; $*$ is the convolution operator; $\delta(t)$ is the Dirac function; ∂ denotes the solution derivative.

Equation (4) is solved by converting the constrained variational issue into the unconstrained variational problem while keeping the constraints unchanged, and the Lagrange multiplier operator μ is introduced to obtain the generalized Lagrange expression.

$$\begin{aligned} L(\{u_L\},\{\omega_L\},\mu) = \beta \sum_l \left\| \partial_t \left[(\delta(t) + j/\pi t)^* u_l(t) \right] e^{-j\omega_l t} \right\|_2^2 \\ + \left\| f(t) - \sum_l u_{l(t)} \right\|_2^2 + \left\langle \mu(t), f(t) - \sum_l u_{l(t)} \right\rangle \end{aligned} \tag{5}$$

where β is the quadratic penalty factor to diminish the intervention of Gaussian noise, and the ADMM iterative algorithm is used to iteratively optimize the modal ingredients and their middle frequencies, and finally get the optimal center frequency corresponding to each modal component, and the expressions of u_l, w_l, and μ are as follows.

$$\hat{u}_l^{n+1}(\omega) \leftarrow \frac{\hat{f}(\omega) - \sum_{i \neq l} \hat{u}_i(\omega) + \hat{\mu}(\omega)/2}{1 + 2\beta(\omega - \omega_l)^2} \tag{6}$$

$$\omega_l^{n+1} \leftarrow \frac{\int_0^\infty \omega \left| \hat{u}_l^{n+1}(\omega) \right|^2 d\omega}{\int_0^\infty \left| \hat{u}_l^{n+1}(\omega) \right|^2 d\omega} \tag{7}$$

$$\hat{\mu}^{n+1}(\omega) \leftarrow \hat{\mu}^n(\omega) + \eta \left(\hat{f}(\omega) - \sum_l \hat{u}_l^{n+1}(\omega) \right) \tag{8}$$

where η is the noise tolerance, n is the number of iterations, and $\hat{u}_l^{n+1}(\omega)$, $\hat{u}_i(\omega)$, $\hat{f}(\omega)$, and $\hat{\mu}(\omega)$ correspond to the Fourier transforms of $u_l^{n+1}(t)$, $u_i(t)$, $f(t)$, and $\mu(t)$, respectively. Where the constraints of the iterative process are as follows.

$$\sum_{l=1}^{L} \left\| \hat{u}_l^{n+1} - \hat{u}_l^n \right\|_2^2 / \left\| \hat{u}_l^n \right\|_2^2 < \xi \tag{9}$$

where ξ is the given accuracy.

According to the above analysis, first initialize the parameters $\hat{u}_l$, ω_l, $\hat{\mu}_l$, set the maximum number of iterations Z; use Equation (6), Equation (7) and Equation (8) to update the number of $\hat{u}_l$, ω_l, $\hat{\mu}_l$, determine whether it meets the Equation (9) or $n \geq Z$, if it does not meet the optimization of the continuation of iteration; if it meets the output of the last parameter $\hat{u}_l$, ω_l, until the obtained sEMG for the monotonic function to stop the decomposition, the number of IMF obtained at this time for the L, then the original signal is decomposed as follows.

$$f(t) = \sum_{l=1}^{L} u_l(t) + \omega_l \tag{10}$$

4. Machine learning-based sEMG recognition in sports injury rehabilitation.

4.1. Feature extraction of sEMG signals. After the VMD denoising of the athletes' sEMG signals, this paper firstly extracts the sEMG characteristics from the time field, frequency field and time-frequency field, and then uses PCA to downsize the sEMG features; finally, the samples are weighted based on the number of samples in different categories, and the PSO method is adopted to enhance the relevant parameters of the traditional SVM algorithm, and the optimal parameters are re-trained to the SVM, and then it is used as the final classifier to efficiently identify the sEMG features in the rehabilitation of sports injuries. Finally, the particle swarm algorithm is used to optimize the relevant parameters of the traditional SVM algorithm, and by retraining the SVM with the optimal parameters, the SVM is used as the final classifier to efficiently recognize the sEMG features in sports injury rehabilitation as shown Figure 2.

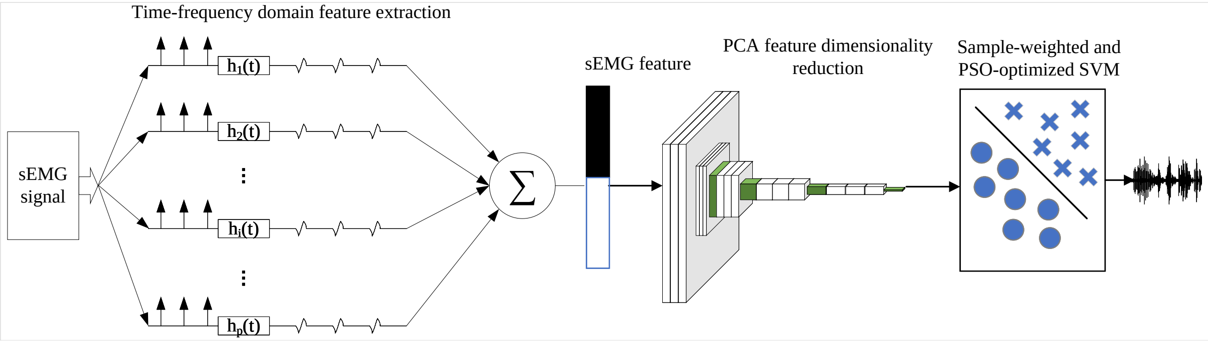

Figure 2. The model for the suggested sEMG identification method

To analyze the information contained in the sEMG signals more comprehensively, this paper extracts the time-domain characteristics, frequency-domain characteristics, and time-frequency-domain characteristics of sEMG.

(1) Time domain feature extraction. The time-domain characteristics used are Root Mean Square (RMS) and Absolute Mean Value (ARV). The formula for calculating the time-domain feature values is as bellow.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} t_i^2} \tag{11}$$

$$ARV = \frac{1}{N}\sum_{i=1}^{N} |t_i| \tag{12}$$

where $t_i (i = 1, 2, \ldots, N)$ is the time series of sEMG.

(2) Frequency domain feature extraction. The frequency domain characteristics selected are mean power frequency (MPF) and median frequency (MF). The formula for calculating the frequency domain feature values is as follows.

$$MPF = \frac{\int_0^\infty w \times PSD(w)dw}{\int_0^\infty PSD(w)dw} \tag{13}$$

$$MF = \frac{1}{2}\int_0^\infty PSD(w)dw \tag{14}$$

where w is the frequency of the sEMG signal and $PSD(w)$ is the power spectral density operation of the sEMG signal.

(3) Time-frequency domain feature extraction. Time-frequency analysis can present the energy signals of EMG signals in both time and frequency domains simultaneously, which is very important for analyzing non-stationary signals. The wavelet transform is used to calculate the instantaneous mean power (IMPF) and instantaneous median frequency (IMF) of EMG signals in the time-frequency domain.

$$IMPF = \frac{\int_{w_1}^{w_2} w \times PSD(t,w)dw}{\int_{w_1}^{w_2} PSD(t,w)dw} \tag{15}$$

$$\int_{w_1}^{IMF} PSD(t,w)dw = \int_{IMF}^{w_2} PSD(t,w) \tag{16}$$

where w is the frequency of the sEMG signal and $PSD(t,w)$ is a two-dimensional function of frequency and time.

4.2. **Dimensionality reduction of sEMG signal features based on PCA..** This article utilizes the 6-channel sEMG signals extracted in the previous section to extract feature vectors in 36 dimensions. Due to the existence of many redundant features in the high-dimensional data, the amount of computation in the experimental process is increased, which has a grand effect on the classifier. At the same time, this process will cause a series of problems such as "overfitting" and "dimensionality catastrophe", which will reduce the performance of the classifier [27]. Therefore, PCA [28] is used for dimension reduction, and the steps in detail are as below.

(1) Decenter the original feature vector x: $x_{output} = (x_{input} - \lambda)/\sigma$, where λ is the mean of the instance data and σ is the standard deviation of the instance data. The output data is a standard normal distribution.

(2) Calculate the matrix eigenvalues of the covariance matrix R and sort them in order from the smallest to the smallest: $\nu_1 \geq \nu_2 \geq \cdots \geq \nu_m \geq 0$, and the eigenvectors $\kappa_1, \kappa_2, ..., \kappa_m$ corresponding to each eigenvalue are sorted in the order of the eigenvalues. Where $\kappa_j = (\kappa_{1j}, \kappa_{2j}, ..., \kappa_{mj})^T$ is the new eigenvector after transformation, the specific form is shown below, y_m is the m-th principal component.

$$\begin{cases} y_1 = \kappa_{11}x_1 + \kappa_{21}x_2 + \cdots + \kappa_{n1}x_n \\ y_2 = \kappa_{12}x_1 + \kappa_{22}x_2 + \cdots + \kappa_{n2}x_n \\ \vdots \\ y_m = \kappa_{1m}x_1 + \kappa_{2m}x_2 + \cdots + \kappa_{nm}x_n \end{cases} \tag{17}$$

(3) Choose the dimension q ($q \leq m$) that retains the new eigenvectors and compute the combined evaluation value. First calculate the information contribution rate of the covariance matrix eigenvalues ν_j ($j = 1, 2, ..., m$): $b_j = \nu_j / \sum_{l=1}^{m} \nu_l$. Then calculate the cumulative contribution of the covariance matrix eigenvalues $\alpha_q = \sum_{l=1}^{q} \nu_l / \sum_{l=1}^{m} \nu_l$. When α_q meets the requirement, only the first q eigenvectors are retained as the principal components for this classification. Finally, the composite score of the first q eigenvectors as principal components is calculated: $S = \sum_{j=1}^{q} b_j y_j$.

(4) Based on the number q of principal components of the identity matrix and construct the principal component matrix.

$$Y_{m\times q} = X_{m\times n} K_{n\times q} \tag{18}$$

where $K_{n\times q} = [\kappa_1, \kappa_2, ..., \kappa_q]$, and finally the principal component feature $Y_{m\times q}$ after dimensionality reduction of the sEMG signal features.

4.3. **Improved SVM-based sEMG signal recognition in sports injury rehabilitation.** After obtaining the dimensionality-reduced sEMG features, this paper utilizes the SVM classifier to classify and identify the sEMG of athletes in sports injury rehabilitation. Since the classification results of traditional SVM algorithm are not accurate when the number of samples is not balanced, this paper weights the samples according to the number of samples in different categories and optimizes the relevant parameters by using particle swarm algorithm [29], so as to achieve the recognition of SEMG by using the optimized SVM.

Suppose $\{(Y_i, Z_i), i = 1, 2, ..., q\}$ is a dataset with q samples of the sEMG signal, where $Y_i \in R^m$ is the m-dimensional feature of the samples and Z_i is the label of the samples. The purpose of classification and identification is to construct a decision function $f(x)$.

$$f(Y) = sgn\left[V\varphi(Y) + a\right] \tag{19}$$

where sgn is the sign function; $\varphi(Y)$ is the high-dimensional mapping function; V is the hyperplane coefficient; and a is the intercept parameter.

$$V\varphi(Y) + a = 0 \tag{20}$$

The traditional SVM uses the penalty parameter g to realize the punishment of misclassification. In the process of optimizing the SVM, a larger penalty coefficient is applied to the important sample points and a smaller penalty coefficient is applied to the unimportant samples, so as to expect the classification accuracy of the whole sample to be improved. When the training instance set is linearly indivisible, a non-negative relaxation variable $\theta_i \geq 0$ needs to be enclosed, and the issue of searching for the optimal categorisation hyperplane of the optimized SVM can be expressed as follows.

$$\min \frac{1}{2}V^T V + g\sum_{i=1}^{l}\theta_i \tag{21}$$

The constraints of Equation (21) are as follows.

$$\begin{cases} Z_i[V^T\varphi(Y_i) + a] \geq 1 - \theta_i \\ \theta_i \geq 0, \quad i = 1, 2, ..., q \end{cases} \tag{22}$$

where s_i denotes the weight of each sample. Solve this quadratic programming issue with linear constraints using the Lagrange multiplier method.

$$L_p = \frac{1}{2}V^T V + C\sum_{i=1}^{q} s_i\theta_i - \sum_{i=1}^{q}\alpha_i\left[Z_i(Y_i^T a) - 1 + \xi_i\right] - \sum_{i=1}^{q}\beta_i\theta_i \tag{23}$$

where α_i and β_i are Lagrange multipliers, and the partial differential is computed so that it equals zero. The minimized dyadic expression is obtained as follows.

$$\min \frac{1}{2}\sum_{i,j=1}^{q}\alpha_i\alpha_j Z_i Z_j K(Y_i, Y_j) - \sum_{i=1}^{q}\alpha_i \tag{24}$$

where $K(Y_i, Y_j) = \varphi(Y_i)\varphi(Y_j)$ is the kernel operation and the decision function is as bellow.

$$f(Y) = sgn\left[V\varphi(Y) + a\right] = sgn\left[\sum_{i\in S_V} Z_i\alpha_i K(Y_i, Y) + a\right] \tag{25}$$

where $a = (1/N_{NSV})\sum_{Y_j\in N_{SV}}\left[Z_i - \sum_{Y_j\in S_V}\alpha_j Z_i K(Y_j, Y_i)\right]$, S_V is the set of support vectors; N_{SV} is the set of standardized support vectors; N_{NSV} is the amount of standardized support vectors.

The key to optimizing the SVM classification algorithm is to choose reasonable weights s_i, when there are only two classes of values, the weights are determined by Equation (26).

$$\frac{s^+}{s^-} = \frac{q^-}{q^+} \tag{26}$$

where q^- and q^+ denote the amount of instances in the positive and negative categories, respectively.

The performance of the optimized SVM model relies on the option of the penalty parameter C and the kernel operation parameter g. The quality of the parameters has an important impact on the accuracy of the algorithm. Therefore, the PSO algorithm is adopted to improve the SVM parameters to ensure that the parameters chosen by the algorithm are the optimal parameters for the model.

(1) In the D-dimensional space, m particles are randomly initialized, i.e., the SVM parameters are encoded to form the initial population.

(2) Input the initialized population into the SVM classifier and obtain the fitness value through training.

(3) Evaluate the computed particle fitness values.

(4) Use *pbest* and *gbest* to describe the PSO optimization SVM penalty parameter C and the kernel operation parameter g, respectively, and decide whether the termination conditions are satisfied.

$$\begin{cases} v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 (pbest_{id}^{k} - Y_{id}^{k}) + c_2 r_2 (gbest_{id}^{k} - Y_{id}^{k}) \\ Y_{id}^{k+1} = Y_{id}^{k} + v_{id}^{k+1} \end{cases} \tag{27}$$

where ω denotes the inertia factor; $d = 1, 2, ..., D$ denotes the spatial dimension; $i = 1, 2, ..., q$ represents the amount of particles; k represents the amount of current iterations; v_{id}^k represents the speed of the i-th particle at the k-th iteration; Y_{id}^k represents the position of the i-th particle at the k-th iteration; $pbest_{id}^k$ represents the individual optimal solution for the i-th particle;

$gbest_{id}^k$ represents the global optimal solution for the i-th particle; c_1, c_2 represents the learning factors; r_1, r_2 represents the arbitrary numbers.

(5) If the optimal parameters obtained do not satisfy the termination conditions, the global optimal speed and global optimal position in the iterative process are updated to form a new population and return to step (2) to continue the computation; when the termination conditions are satisfied, the optimal parameters are used to retrain the SVMs, which are then used as the final classifiers for the feature recognition of the sEMGs.

5. Performance testing and analysis.

5.1. Classification performance analysis. In this paper, the performance of the suggested method is experimentally validated in the NinPro DB1 dataset, which contains a total of 12 categories of wrist and leg rehabilitation exercises with different force patterns, and MIT-KNN [14], ULJ-BP [16], GA-SVM [21] and DPSO-SVM method of this article, are trained and tested respectively. Cross-validation is used to demonstrate the actual accuracy of the sEMG classification method, with a sample size of 30 for a single action and a total of 360 samples, where 70% of the samples are arbitrarily chosen for the training set and the remaining 30% for the test set. The hardware parameters used were 5 GHz Intel Core i7-11390H processor, 16 GB RAM and Windows 10 operating system. The experimental program was implemented using the Python programming language.

This article will use Accuracy, Precision, Recall, Harmonized Mean F1 and Correlation Coefficient R [30] as the metrics to measure the recognition performance. Figure 3 demonstrates the experimental results comparing the comprehensive performance of different methods for recognition. The Accuracy, F1 and R of the DPSO-SVM are 0.942, 0.951 and 0.985, which are 16.7%, 16.6% and 20.4%, respectively, and 16.4% and 4.3%, respectively, compared to the MIT-KNN, 16.6% and 20.4%, respectively, compared to

ULJ-BP, and improved by 13.1%, 11.8% and 16.3%, respectively, compared to GA-SVM, and improved by 4.6%, 3.7% and 4.9%, respectively.

MIT-KNN performs the worst because it utilizes the KNN algorithm to classify and identify sEMGs without denoising and dimensionality reduction, which results in a poor classification effect. ULJ-BP performs the second worst because its algorithm is the process of searching for the optimal solution for a large number of samples, which is a process of statistical computation, and the training speed is relatively slow due to the repeated and iterative learning. GA-SVM performs second best because it optimizes SVM through the GA algorithm, which acts as a classifier to some extent, but the accuracy is lower than that of DPSO-SVM, which does not deal with the redundant features. Therefore, in terms of various performance indicators, the recognition accuracy of the DPSO-SVM is better than that of the other three models.

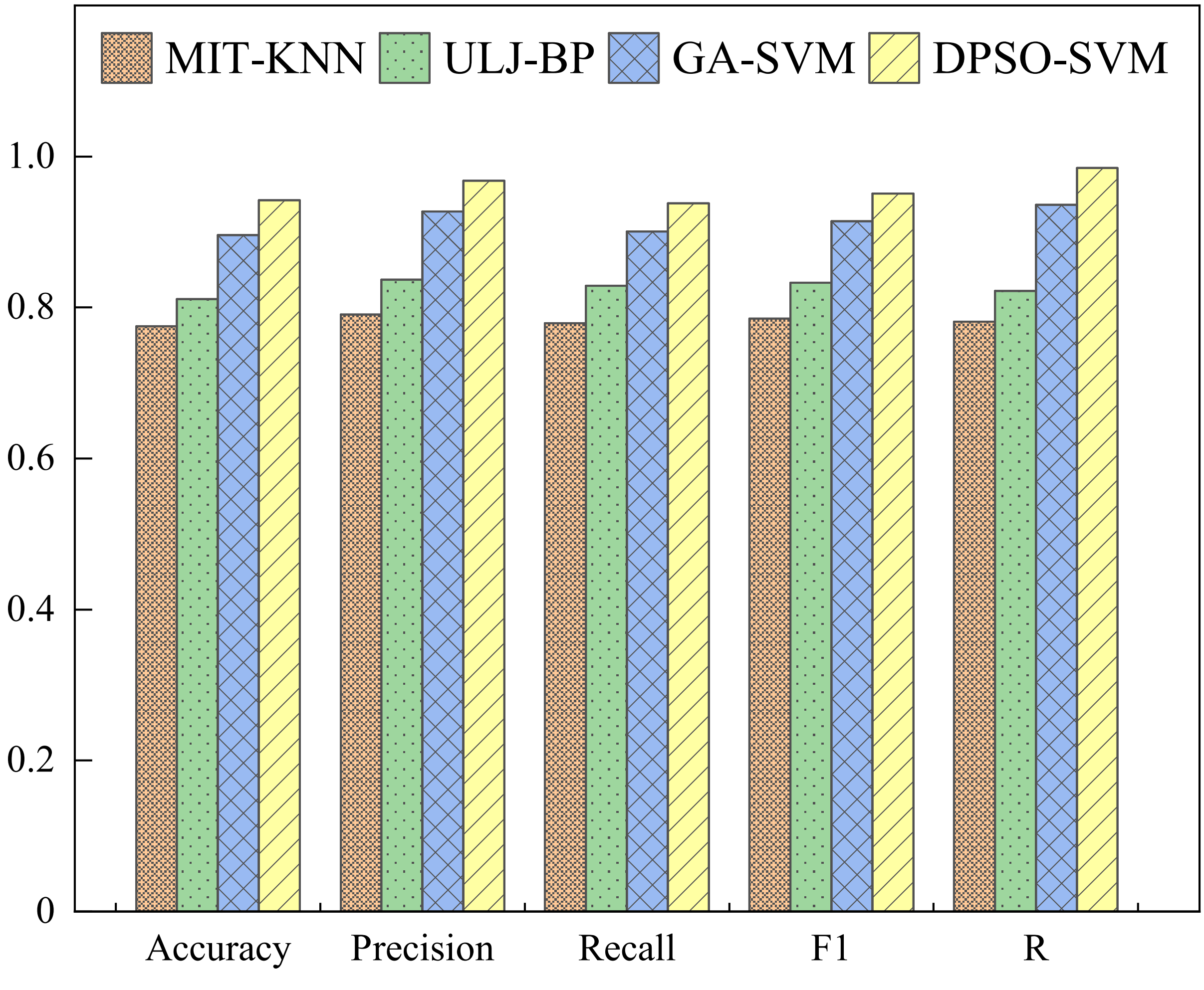

Figure 3. Comprehensive performance comparison of different methods of identification

To compare the performance of different EMG signal recognition models in sports injury rehabilitation, three models were tested with test data. The probability of each state in the test sample is obtained for each action state, and the false positive rate and true positive rate of the corresponding category can be calculated by calculating the probability matrix and labeling matrix, and a ROC curve is plotted. In each action state, the ROC curve of the corresponding category is generated, and the ROC curve of each state is averaged. Finally, the ROC curves of each recognition model are obtained, as shown in Figure 4. The ROC curves of the DPSO-SVM model and the area enclosed by the horizontal coordinates are larger than those of the other models, and the overall recognition rates of DPSO-SVM, MIT-KNN, ULJ-BP, and GA-SVM are calculated to be 95.52%, 79.57%, 81.44%, and 92.17%, respectively, and the overall composite recognition rate of DPSO-SVM is higher than that of other models.

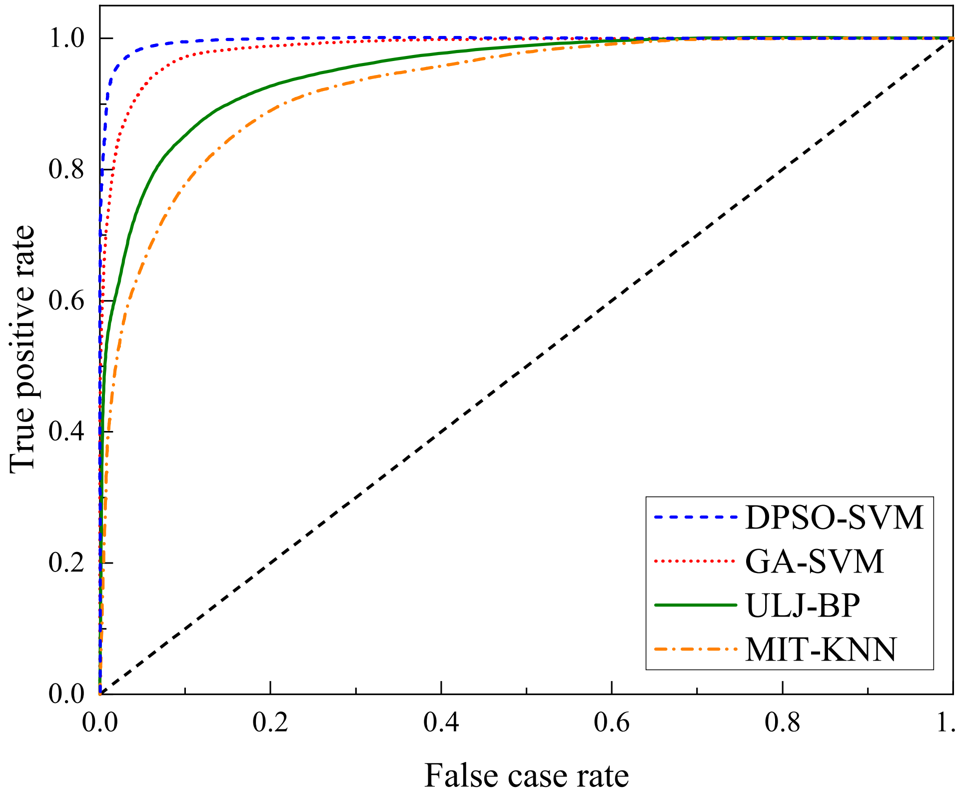

Figure 4. Sample ROC curves for 4 model tests

5.2. Feature dimensionality reduction analysis. This article compares the average classification accuracy and average training time of the four recognition methods without dimensionality reduction and after dimensionality reduction, as implied in Table 1.

Table 1. Average categorisation accuracy of undimensioned and dimensioned sEMG Data

Method	**Average classification accuracy**		**Average training time (s)**	
	Undimensionalized	Lower dimensional	Undimensionalized	Lower dimensional
MIT-KNN	0.775	0.835	2189.03	713.48
ULJ-BP	0.782	0.811	1009.49	284.46
GA-SVM	0.896	0.922	260.9	100.42
DPSO-SVM	0.901	0.945	140.1	33.08

As can be seen from Table 1, the average classification accuracy after dimensionality reduction is higher than that without dimensionality reduction, no matter on MIT-KNN, ULJ-BP, GA-SVM and DPSO-SVM classification models; therefore, there is a redundancy of information in the unreduced data, which is not conducive to the recognition, so it is necessary to carry out the characteristic selection for the categorisation of sEMG in the rehabilitation of sports injuries. By dimensionality reduction of the data, the training time is greatly reduced, which improves the training efficiency of the classification model.

In addition, the average classification accuracy and average classification time of DPSO-SVM are better than those of the comparison methods in both non-dimensionalized and dimensionalized cases. DPSO-SVM combines the sample weighting and particle swarm algorithms to optimize the sample data when mapping the sample data to the sample feature space, and indirectly optimizes the process by finding the optimal kernel function parameter, so as to eliminate the problem of excessive computation of traditional SVM algorithms in the process of processing sample data. Comparing the performance of the improved SVM classification model, it can be seen that the optimization of SVM by PSO algorithm improves the problem of small samples, and thus improves the classification accuracy and recognition speed of the model.

6. **Conclusion.** Existing recognition methods based on sEMG in sports injury rehabilitation are susceptible to noise interference, which makes the feature extraction of sEMG insufficient and leads to low recognition efficiency. Aiming at the above deficiencies, this article designs a machine learning-based sEMG recognition method in sports injury rehabilitation. Firstly, using the VMD to add the ADMM iterative algorithm to decide the center frequency and bandwidth of all components of the SEMG signal, for the goal of realizing the frequency domain segmentation of the signal and the efficient separation of all modal components, reduce the complexity and nonlinearity of the SEMG, and diminsh the interference of Gaussian noise. Next, the time-domain characteristics, frequency-domain characteristics and time-frequency-domain characteristics are extracted from the sEMG. Then the extracted sEMG feature vectors are dimensionality reduced using PCA, and finally the relevant parameters of SVM are optimized using sample weighting and particle swarm algorithm, and the optimized SVM is used to classify and recognize the dimensionality-reduced sEMG features. The experimental outcome implies that the suggested method has higher accuracy and lower classification time for sEMG recognition compared to other recognition methods.

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