An Improved SVM Method for Movement Recognition of Lower Limbs by MIMU and sEMG

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***Abstract*—Aiming at the problems that the movement recognition accuracy of lower limbs needs to be improved, the optimized SVM recognition method by using voting mechanism is proposed in this paper. First, CS algorithm is applied to optimize the kernel function parameter and the penalty factor for SVM model. And then, voting mechanism is used to ensure the recognition accuracy of SVM classification algorithm. Finally, the experiments have been implemented and different classification algorithms have been compared. The recognition results shows that the movement recognition accuracy for the lower limbs by the optimized SVM recognition algorithm using voting mechanism is about 98.78%, which is higher than other commonly used classification algorithm with or without voting mechanism. The recognition method for the lower limbs proposed in this paper can be used in the field of rehabilitation training, smart healthcare and so on.**

Keywords—Surface electromyography; micro inertial measurement unit; support vector machine; voting mechanism

I. Introduction

Along with the development of artificial intelligence technology, many researchers have focused on the study of human posture recognition [1-4]. Recognition for the movements of lower limbs is widely used in the field of rehabilitation training, physical exercise and so on [5].As for the current research, there are many sensors used for the recognition of lower limbs, such as visual sensors, inertial sensors, surface electromyographic sensors, etc.

In the study of human behavior recognition using visual sensors, Nie proposed a view-invariant method for human action recognition by recovering the corrupted skeletons based on a 3D bio-constrained skeleton model and visualizing those body-level motion features obtained during the recovery process with images [6]. Based on the Northwestern-UCLA dataset, the classification accuracy of the 10 action images in the proposed algorithm is about 94.40%. Nieto-Hidalgo proposed an extraction system by analyzing image sequences to identify human gait features [7]. The recognition accuracy for the normal and abnormal gaits are both more than 90.00%. Based on the Kinect sensor, Min proposed an indoor fall detection method using SVM method according to the 3D skeleton joint array information [8]. The experiment result shows that the fall recognition accuracy is about 92.05%. Liu proposed an algorithm for human behavior recognition using skeletal joint information of deep sequences [9]. The angle and position information between joints were captured by RGB video, and the obtained feature vectors were used as the input of the classifier. The experimental results showed that the average accuracy of behavior recognition is 95.00%. It is convenient to recognize the human behavior by using visual sensors, but the environment illumination, image resolution, and autofocus speed will affect the recognition accuracy. What's more, the huge amount of image processing will increase the hardware cost.

In the study of human behavior recognition using inertial sensors, Khatun proposed a sensor-based learning method for human activity recognition [10] based on a hybrid deep learning model coupling convolutional neural network and long and short term memory network. The system is based on the data set (H-Activity) collected by the smart phone sensor. The experimental results show that the accuracy of the self-collected data set trained by this method is 99.93%, and the accuracy of the model trained by the benchmark data set (MHEALTH) is 98.76%. Zhang proposed a SVM algorithm based on magnetometer and gyroscope sensors to classify the human motion postures [11]. Experimental results show that the average recognition accuracy for human motion posture is about 90.80%. Marron proposed a smart phone system with embedded inertial sensors in an indoor environment [12], in which the information of human biomechanical models is combined. The recognition average accuracy for human behavior is 95.00%. Guo proposed a novel monitoring framework of human motion sequences based on wearable inertial sensors [13], the recognition process can be divided into data acquisition, segmentation and recognition stages. At the recognition stage the HMM algorithm is used to recognize the motion sequence. The experimental results show that the average recognition accuracy for human movement is 92.75%. As for the inertial sensors used for the recognition of human behavior, it has the advantages of high efficiency, but the installation will affect the recognition accuracy.

In the study of human behavior recognition using surface electromyography (sEMG) sensors, Qi proposed a gesture recognition system based on the principal component analysis method and GRNN neural network [14]. By extracting the key information of human gestures, the specific action mode can be identified. Experiment results show that the system's overall recognition accuracy for 9 static gestures is about 95.10%. Zhang proposed a dynamic adaptive neural network algorithm based on multi-feature fusion of surface EMG signals [15] to achieve accurate recognition of eight lower limb movements (walk (WK), left turn (TL), right turn (TR), stand up (TP), sit down (ST), go upstairs (UPS), go downstairs (DWS) and jog (CD)). Experimental results show that the recognition accuracy of this method is 94.89%. As for the application of sEMG sensors, human behavior recognition can be easily affected by some irregular movements of the human body, such as when somebody suddenly falls, it may cause a significant change in the sEMG signal of the leg muscles, which will affect the judgment of human leg movements.

From the aforementioned methods for the recognition of human behavior recognition, the accuracy still needs to be improved. In this paper, take the features of lower limbs into consideration, the improved SVM algorithm is proposed for the recognition of lower limbs by MIMU and sEMG sensors. First, in order to obtain the parameters of kernel function and penalty factor, Cuckoo search algorithm (CS) is used to optimize SVM model. Then, the voting mechanism is applied to improve the recognition accuracy of SVM algorithm. Finally, the experiment is carried out to verify the validity of the proposed method by seven movements of lower limbs.

II. CLASSIFICATION ALGORITHM

A. SVM Classification Algorithm

As for the complexity of the movements of low limbs, it is difficult to recognize the movements directly from the outputs of MIMU and sEMG. Thus, it is necessary to extract the features of the outputs and then use a kind of mapping algorithm to separate the features from the low dimensional space to a high dimensional space. SVM classification algorithm based on the principle of structural risk minimization has the advantages of good generalization ability [16-18]. In this paper, according to the features of outputs of MIMU and sEMG and take the complexity of the algorithm calculation into consideration, SVM classification algorithm is used.

As for SVM classification algorithm, suppose the sample set is D={$(x_1,y_1),(x_2,y_2),\ldots,(x_m,y_m)$}, where, $x_i \in R^n$, $y_i \in \{-1,1\}$, m is the number of samples. $\phi(x_i)$ is the eigenvector after mapping. Then, the hyperplane is established for classification by:

$$f(x) = W\phi(x_i) + b \tag{1}$$

Where, W is the normal vector of the optimal hyperplane, b is the displacement. The problem to solve the optimal hyperplane can be converted by:

$$\begin{cases} \min\left(\dfrac{1}{2}\|W\|^2 + c\sum_1^m \xi_i\right) \\ s.t. \quad y_i\left[W^T\phi(x_i)+b\right] \ge 1-\xi_i \end{cases} \tag{2}$$

Where, ξ_i is the relaxation variable, c is the penalty factor. Introducing the Lagrange multiplier α_i by:

$$\begin{cases} \max\left[\sum_1^m \alpha_i - \dfrac{1}{2}\alpha_i\alpha_j y_i y_j \kappa(x_i,x_j)\right] \\ s.t. \quad \sum_1^m \alpha_i y_i = 0, c \ge \alpha_i \ge 0, i=1,2,\ldots,m \end{cases} \tag{3}$$

Where, $\kappa(x_i,x_j)$ is the kernel function. And in this paper, the gaussian radial basis function is selected by:

$$\kappa(x_i,x_j) = \phi(x_i)^T\phi(x_j) = \exp(-g\left\|x_i - x_j\right\|^2) \tag{4}$$

Where, g is the kernel function parameter. Then, solving (3) and the following solution can be obtained:

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^m \alpha_i^* y_i \kappa(x_i,x_j) + b^*\right) \tag{5}$$

In the process to solve the hyperplanes, the kernel function parameter g and the penalty factor c are the key parameters for SVM classification model. Thus, it is necessary to get the best kernel function parameter g and the penalty factor c for the SVM classification model to recognize the movements of the lower limbs.

B. CS Algorithm

CS Algorithm is a heuristic algorithm, which solves the optimal parameters by simulating the parasitic brooding behavior of cuckoo birds [19,20]. It has the advantages of few parameters and fast convergence speed, so it is widely used for parameter optimization.

As for the parameter optimization of the kernel function parameter g and the penalty factor c, the finding probability p_a in CS algorithm will balance the local random optimization and global random optimization. The local random optimization will updates the position of the nest $z=[g\ c]^T$ as follows:

$$z_i(n+1) = z_i(n) + \alpha s \otimes \mathrm{H}(p_a - \varepsilon) \otimes (z_j(n) - z_i(n)) \tag{6}$$

Where, $z_i(n+1)$ represents the position of the nest i updated at the $(n+1)$ times of iteration, $z_j(n)$ is the nest selected by random substitution, α is the step scale factor, s is the step size, H(u) is the unit step function, ε is a random number.

Then, the global random optimization will update the position of the nest $z=[g\ c]^T$ by:

$$z_i(n+1) = z_i(n) + \alpha L(s,\lambda) \tag{7}$$

Where, L(s,λ) is the Levy distribution. λ is a constant and in this paper it is 1.5 for the parameter optimization in CS algorithm.

As for the $(n+1)$ times of iteration, the position of the nest will be updated, and it will be used as the input for the next iteration. According to the finding probability p_a, the highest accuracy nest $z=[g\ c]^T$ for the whole nests will be obtained.

C. *Voting Mechanism*

Voting mechanism proposed in this paper is a combination strategy for the movement recognition of lower limbs. The basic idea of it is using a sliding window to select the most recognition output label by the machine learning algorithm as the recognition output label for the middle position of this sliding window. Thus, it can correct the error recognition label.

The hardware for the recognition of the lower limbs in this paper is self-designed and the sampling frequency for the output data is 150Hz. According to the experiment for a consecutive movement of lower limbs, the self-designed hardware can collect at least 75 groups of output data. For the same movement recognition of lower limbs, it should be the same output label when using machine learning recognition algorithm. However, for the different movement recognition of lower limbs, the voting mechanism is necessary by the sliding window to identify and correct the error recognition label.

III. Experiment for Movements of Lower Limbs

In order to verify the efficiency of the proposed optimize SVM classification algorithm, the movement recognition experiments for the lower limbs have been carried out. The designed recognition flow is shown in Fig. 1.

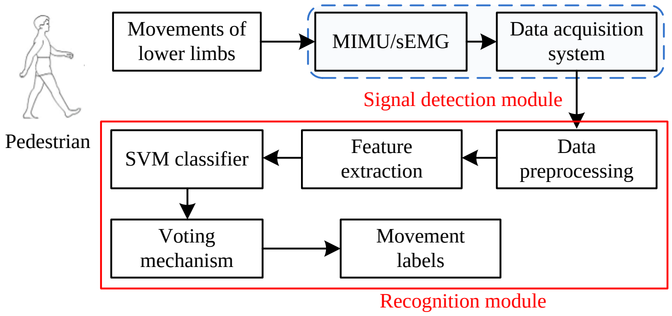

Fig. 1. Recognition flow for the lower limbs

The outputs of MIMU and sEMG will be collected by the signal detection module. And then the outputs will be preprocessed, during this process, the median filter is used to preprocess the outputs of the sensors which will remove the noise. Then, the features will be extracted by the mean absolute average (MAV) before they were sent to SVM classifier. What's more, the voting mechanism will be carried out to ensure the recognition accuracy. Finally, the movement labels for the movement of lower limbs will be shown.

A. *Hardware for the Experiment*

The self-designed hardware for the recognition of the lower limbs is shown in Fig. 2.

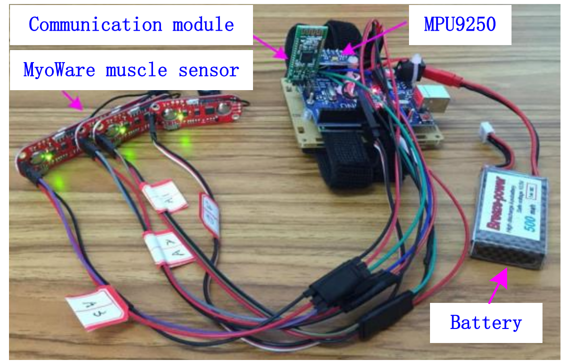

Fig. 2. Hardware for the experiment

MPU9250 and MyoWare muscle sensor is used for MIMU and sEMG. And the self-designed hardware will be worn on the lower limbs as shown in Fig. 3.

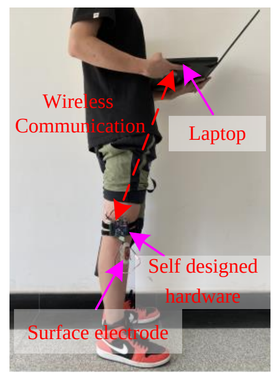

Fig. 3. Hardware worn on the lower limb

The muscles selected for the experiment should be close to the skin surface and there should be large enough to place the electrodes. Thus, we choose the tibialis anterior, extensor digitorum longus, gastrocnemius muscle, and soleus muscle to place the sEMG electrodes for the reason that the muscular contraction is obvious when there's movement of the lower limbs.

B. *Definition of Movements of Lower Limbs*

In this paper, there are seven movements of lower limbs needs to recognize, which are defined in Table I.

TABLE I. Movements Of Lower Limbs

Movements of lower limbs	**Labels**
stand still	1
mark time	2
run with raised legs	3
go straight	4
run with speed	5
walk up the slope	6
walk down the slope	7

C. Recognition Test

There are 1072 sets data collect, we choose 872 sets of data as a fixed training set randomly, and then the following 200 sets of data are selected as the test set.

CS algorithm is used to optimize kernel function parameter g and the penalty factor c for SVM classification algorithm. As for CS algorithm, the number of parameters need to be optimized is 2, the number of nests is 20, the finding probability p_a is 0.25, the iteration time is 50, the upper bound of g and c is 10, and the lower bound is 0.01. Then, SVM classification model can be established.

As for the recognition, 30 independent recognition tests have been carried out based on 200 sets of data. Fig. 4 and Fig. 5 have illustrated one of the recognition results for the proposed optimized SVM classification model with and without voting mechanism.

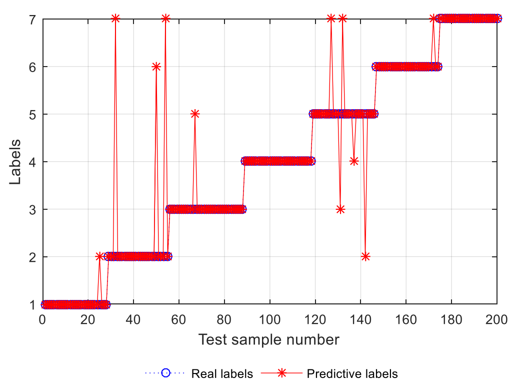

Fig. 4. SVM classification without voting mechanism

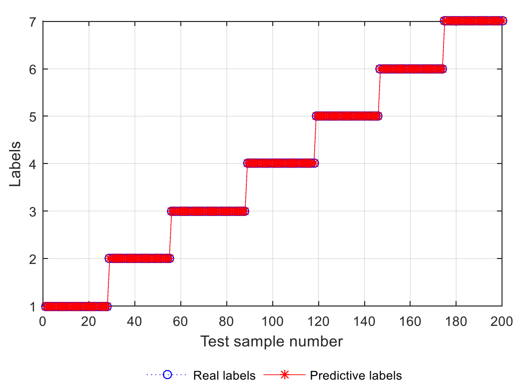

Fig. 5. SVM classification with voting mechanism

As show in Fig. 4 and Fig. 5, it is obvious that the recognition accuracy has been improved when voting mechanism is used to correct the wrong movements' labels of lower limbs labels.

In order to verify the effectiveness of the proposed optimized SVM recognition method in this paper, the most commonly used algorithm for human motion recognition has been applied, such as generalized regression neural network (GRNN), probabilistic neural network (PNN), and extreme learning machine (ELM). 30 independent recognition tests have been performed by using the above algorithms with and without voting mechanism. The recognition accuracy is shown in Fig. 6 and Table II.

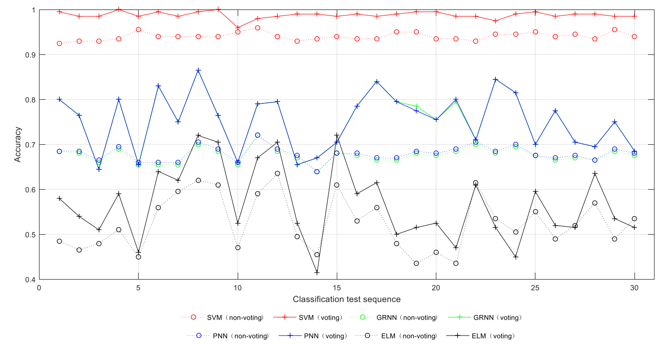

Fig. 6. Recognition accuracy for voting and non-voting mechanism

TABLE II. STATISTICAL RESULTS FOR THE RECOGNITION

Recognition Methods		**Standard Deviation**	**Average accuracy**	**Coefficient of Variation**
optimized SVM	Non-voting	8.55×10^{-3}	94.05%	9.09×10^{-3}
	voting	7.73×10^{-3}	98.78%	7.83×10^{-3}
GRNN	Non-voting	1.66×10^{-2}	67.57%	2.46×10^{-2}
	voting	6.32×10^{-2}	75.28%	8.40×10^{-2}
PNN	Non-voting	1.66×10^{-2}	67.97%	2.44×10^{-2}
	voting	6.32×10^{-2}	75.27%	8.40×10^{-2}
ELM	Non-voting	6.03×10^{-2}	52.47%	1.15×10^{-1}
	voting	8.30×10^{-2}	56.77%	1.46×10^{-1}

Fig. 6 and Table II show that the average recognition accuracy of lower limbs by the optimized SVM recognition method is higher than other commonly used algorithm for human motion. What's more, the recognition accuracy by the voting mechanism is higher than that without voting mechanism.

For the statistical results of 30 independent recognition tests show in Table II, the standard deviation and the coefficient of variation for the proposed optimized SVM recognition method with the voting mechanism are the minimum values in the above methods, which indicate the stability of the proposed method.

IV. CONCLUSION

Aiming at the problems that the recognition accuracy and stability for the movements of lower limbs need to be improved, the optimized SVM recognition method by using voting mechanism is proposed in this paper. CS algorithm is used to optimize kernel function parameter g and the penalty factor c for SVM classification algorithm. Then, voting mechanism is carried out to ensure the recognition accuracy. Experiments have been implemented and different classification algorithms have been compared. The recognition results illustrated that the recognition accuracy by the optimized SVM recognition algorithm is higher than other recognition algorithms, which demonstrates the validity of the proposed optimized SVM recognition algorithm. And the accuracy for the recognition algorithm with the voting mechanism is higher than the algorithm without the voting mechanism, which demonstrates the effectivity of the voting mechanism. The recognition method for the movement of lower limbs by MIMU and sEMG can be used for the application of smart healthcare, rehabilitation training of lower limbs and so on.

ACKNOWLEDGMENT

This study was supported by Zhejiang Provincial Natural Science Foundation of China Grant Number LQ20F030019. And it was supported by the National Natural Science Foundation of China Grant number 62203393.

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