Abstract—Rehabilitation level evaluation is an important part of the automatic rehabilitation training system. As a general rule, this process is manually performed by rehabilitation doctors using chart-based ordinal scales which can be both subjective and inefficient. In this paper, a novel approach based on ensemble learning is proposed which automatically evaluates stroke patients’ rehabilitation level using multi-channel sEMG signals to this problem. The correlation between rehabilitation levels and rehabilitation training actions is investigated and actions suitable for rehabilitation assessment are selected. Then, features are extracted from the selected actions. Finally, the features are used to train the stacking classification model. Experiments using sEMG data collected from 24 stroke patients have been carried out to examine the validity and feasibility of the proposed method. The experiment results show that the algorithm proposed in this paper can improve the classification accuracy of 6 Brunnstrom stages to 94.36%, which can promote the application of home-based rehabilitation training in practice.

I. INTRODUCTION

Stroke is the main cause of adult disability, which brings a heavy burden to family and society [1]. As the far end of the body, the hand is the most difficult to recover. Therefore, hand rehabilitation is essential for stroke patients [2]. Researches show that the rehabilitation robot is an efficient rehabilitation training method, which can not only improve the efficiency of rehabilitation but also reduce the burden of rehabilitation doctors [3], and some studies also show that home-based rehabilitation training can not only improve the recovery efficiency of patients, but also greatly reduce the medical cost and solve the problem of medical resource shortage [4]. Consequently, the development of a home-based hand rehabilitation robot system is the main solution to improve rehabilitation efficiency, and one of the key elements to achieve this solution is to establish a standardized assessment system, which can assess the degree of patient injury and continuously track patients’ rehabilitation progress [5].

Researches show that improper rehabilitation training is ineffective or even causes secondary harm, so it is important to accurately understand the physical condition of patients and make appropriate rehabilitation strategies [6]. In generally, rehabilitation level assessment is performed manually by experienced rehabilitation doctors using chart-based ordinal scales such as Brunnstrom stages of recovery, Fugl-Meyer Assessment(FMA), Barthel Index(BI) and National Institutes of Health Stroke Scale(NIHSS) [7]. These methods are semi-quantitative evaluation methods, which are inefficient and subjective. More objective and quantitative rehabilitation assessment methods are needed in clinic. In order to obtain fine hand motion information, Fang et al. proposed using infrared imaging equipment to obtain fine hand motion information [8]. Compared with obtaining hand motion information by vision, more cost-effective and easy-to-operate evaluation technology based on sEMG is gradually emerging [9].

The sEMG signal is an electrical signal of muscle activity collected from skin, and the sEMG signal of forearm can truly reflect the movement of patient's hand. A novel approach of Brunnstrom stage automatic evaluation for stroke patients by using multi-channel sEMG is proposed in this paper. The method first selects out the actions suitable for rehabilitation evaluation from nine rehabilitation training actions, and then constructs the rehabilitation evaluation model based on stacking ensemble learning method. This method can be used to evaluate the rehabilitation level while the patients are undergoing rehabilitation training, so as to realize real-time monitoring of the recovery of the hand movement function of the patients and provide basis for timely adjustment of the rehabilitation strategy. Finally, 24 patients’ sEMG data are used to verify the effectiveness of the method.

II. EXPERIMENTS AND METHODS

Fig. 1 presents the system diagram of a home-based hand rehabilitation robot based on sEMG, which mainly includes: patients at different Brunnstrom stages, sEMG data acquisition equipment, microcomputer, motion intention recognition algorithm, rehabilitation level evaluation algorithm, and hand rehabilitation training robot. Among them, the algorithm of rehabilitation evaluation is the basis of making rehabilitation
training strategy and tracking rehabilitation progress. Hence, in the next section, we will focus on the experimental process of patients’ sEMG data collection and the algorithm of Brunnstrom stage automatic evaluation for stroke patients by using multi-channel sEMG proposed in this paper.

A. Experimental Data Collection

In this experiment, MYO (Thalmic Lab, Canada), a sEMG sensor is applied to collect the forearm sEMG signals of 24 stroke patients at different Brunnstrom stages in the rehabilitation center of Shenzhen Hospital of China Medical University and the experimental procedures involving human subjects described in this paper are approved by the Institutional Review Board. The signal sampling rate is 200Hz, and the output is at 50Hz after the underlying hardware sampling reduction processing. MYO is composed of eight dry electrode acquisition modules, which can simultaneously acquire eight channels of sEMG data and six axis attitude data. In order to guarantee the reliability and real-time of evaluation results, patients had to undergo the rehabilitation assessment and cognitive impairment test by rehabilitation doctors before data collection. By communication with the rehabilitation doctors, nine kinds of hand rehabilitation training actions suitable for patients are selected, which are fist, open hand, ulnar deviation, hook grip, radial deviation, palm flexion, dorsiflexion and forearm pronation.

Before the process of data collection, the experimenter will explain the experiment process to the patient and enough time will be left for them to practice these actions. In order to obtain high-quality sEMG data, the skin surface is removed dead skins and cleaned excess oils with gauze and alcohol before myoelectric sensor was worn in the standard way shown in Fig. 2. According to the wearing position of MYO and the anatomy of human forearm, the sEMG signals collected in this paper mainly come from the extensor carpi radialis brevis, radiocarpus, brachioradialis, musculus flexor digitorum, ulnar extensor carpi, extensor digitorum.

![Figure 2. Wearing mode of myoelectric sensor myo](image)

**TABLE I. EXPERIMENTAL PARADIGM OF PATIENTS’ sEMG SIGNAL COLLECTION**

<table>
<thead>
<tr>
<th>Serial number</th>
<th>Action</th>
<th>Action time(s)</th>
<th>Rest time(s)</th>
<th>Repeat number</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Fist, hook grasp, palmar flexion</td>
<td>6</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>2</td>
<td>radial deviation, forearm pronation</td>
<td>6</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>3</td>
<td>open hand, dorsiflexion</td>
<td>6</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>ulnar deviation, forearm supinated</td>
<td>6</td>
<td>4</td>
<td>6</td>
</tr>
</tbody>
</table>

Table I is the experimental paradigm for collecting sEMG in this paper. the time of rest and other actions is 4s and 6s, and the rest is transitional state of interval between other actions. Each patient needs to do 4 groups of movements in total, each group of movements repeated 6 times. All actions in a group are completed in a cycle, each group needs to collect 6 times, so each patient needs to collect 24 times in total.

B. Data Preprocessing and Feature Extraction

The amplitude of sEMG data collected by patients with different Brunnstrom levels is distinct. For the sake of reducing the error caused by the amplitude difference of individual sEMG data, each patient's sEMG data are normalized. Afterwards the sEMG data of 24 patients were fused based on the action labels and split into a training set and a test set according to a ratio of 8: 2.

In order to improve the generalization performance of the classification model, in this paper, all the raw sEMG data is preprocessed recruiting windowing technique in the form of adjacent windowing. We use an incremental window processing scheme, in which the set window length is 200ms and the sliding step length is 60ms (corresponding to \( LW=10, Ll=3 \)). Six prominent features in the field of EMG signal are selected: mean absolute value (MAV), slope sign change (SSC), zero crossing (ZC), wave form length (WL), root mean square (RMS), skewness.

C. Ensemble Learning Method

Compared with the single model method, the ensemble learning method can significantly improve model performance. Ensemble learning methods are mainly divided into three categories: bagging, boosting and stacking. Among them, the main idea of the stacking method is to take the prediction of the first-stage base model as the feature of the next-level fusion model. Fig. 3 is a block diagram of the stacking integrated learning method. Compared with the first two methods, this method can reduce the variance and bias of the model at the same time [10].

![Figure 3. The block diagram of stacking method](image)

Due to the patient's sEMG data has a low signal-to-noise ratio and a small number of samples, it is difficult to obtain a model with low variance and bias using bagging or boosting method. Therefore, stacking method is used in this paper, and Gradient stacking Decision Tree(GBDT), Random Forest (RF), AdaBoost(ADA) and Extra Trees(ET) are used as base classifier and Logistic Regression(LR) as fuser. The base classifier uses a strong model to combine important advanced features, and the fusion classifier uses a weak classifier to avoid overfitting, so as to achieve the balance of variance and deviation.

D. Method of Action Selection for Rehabilitation Evaluation

In order to achieve the goal of simultaneous rehabilitation evaluation in the process of rehabilitation training, the appropriate rehabilitation evaluation actions are selected from
the above nine rehabilitation training actions. The traditional method is to select some common actions as rehabilitation assessment actions, which will cause the deviation of assessment. To solve this problem, the relationship between rehabilitation level and rehabilitation training actions of patients is analyzed, and the most relevant action is selected as the rehabilitation assessment actions.

E. Rehabilitation Evaluation Method Based on sEMG

The block diagram of Brunstrom stage automatic evaluation for stroke patients by using multi-channel sEMG proposed in this paper is shown in Fig. 4. The algorithm consists of two parts: offline model training and online rehabilitation evaluation. Compared with other methods of automatic evaluation of rehabilitation level, the method proposed in this paper can automatically evaluate the rehabilitation level when the patients are in rehabilitation training, thus avoiding the extra process of rehabilitation evaluation. The accuracy of rehabilitation evaluation is improved by screening the rehabilitation evaluation actions and using stacking ensemble learning method.

III. RESULTS AND DISCUSSION

In order to verify the effectiveness of the Brunstrom stage automatic evaluation algorithm by using multi-channel sEMG proposed in this paper, two groups of experiments were carried out: a) action selection experiment of rehabilitation evaluation; b) comparative experiment of ensemble learning model and other models for rehabilitation evaluation. Next, we will introduce the content of the two sets of experiments in detail and discuss the results in detail.

A. Selection of Rehabilitation Assessment Actions

In order to select the actions that are suitable for the rehabilitation evaluation of patients, sEMG data of 24 patients were divided according to the rehabilitation level, and the data of each level of patients were fused according to the action category. Next, the sEMG data of each level of patients were preprocessed and extracted as described above. Then, the training set was used to train the stacking ensemble model, and the trained classification model was evaluated on the training set and the test set respectively, and the average of the 5-fold cross-validation results was used as the index for model evaluation. Finally, the results of each level of patient classification model in the test set were counted, and the relationship between the patients’ rehabilitation level and the action category is shown in Fig. 5, where the horizontal axis represents the patients’ rehabilitation level, the vertical axis represents the patients’ rehabilitation training action category, and the middle value is the average accuracy of the model.

As can be seen from Fig. 5, the accuracy of actions recognition of patients increases with the increase of rehabilitation level, which is consistent with the expectation. In addition, the experimental results show that patients at different Brunstrom stages have different optimal actions. Therefore, according to the results of Fig. 5 and the peculiarities of patients’ rehabilitation level, the rehabilitation training scheme can be determined. Those with high action recognition rate are used for active rehabilitation training, and the rest are used for passive rehabilitation training, as shown in Table II.

In order to select the actions suitable for the rehabilitation level evaluation, the correlation between the actions and rehabilitation level was explained by calculating the variance of the accuracy of the classification model corresponding to six Brunstrom levels under each action in this paper, and the rehabilitation level, and the results are shown in Fig. 6. The vertical axis represents the category of rehabilitation training actions, and the horizontal axis represents the differentiation between rehabilitation levels under the actions. It can be seen from the experimental results that there is a big difference between the rehabilitation levels under the hook grip and the forearm supination. Therefore, hook grip and forearm supination are selected as the rehabilitation level evaluation actions.


B. Results of Rehabilitation Level Assessment

For the sake of proving the effectiveness of the selected rehabilitation actions in the previous experiment and the stacking ensemble learning method proposed in this paper, the results of the Brunnstrom stages classification with different classification models for nine rehabilitation training actions were compared. In this paper, the sEMG data of 24 patients were preprocessed and feature extracted as described above. Then, the following machine learning model was trained with the training set: Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), LR, ET, GBDT, ADA, RF and stacking ensemble learning model. Finally, the classification accuracy of the model on the test set is shown in Fig. 7, where the horizontal axis represents the model, the vertical axis represents the rehabilitation training action, and the middle value represents the average classification accuracy of the Brunnstrom classification model on the test set under a certain rehabilitation training action.

![Figure 7. Accuracy results of rehabilitation level evaluation under different rehabilitation training actions](image)

As can be seen from the experimental results in Fig. 7, in most of the classification models, the classification accuracy of rehabilitation level is the best under the actions screened out in the previous experiment. Especially when using the forearm supination and stacking ensemble learning model, the accuracy of offline classification on the test set of the 6 types of Brunnstrom grades is as high as 94.36%, and when using the palm flexion and stacking ensemble learning models, the offline classification accuracy of the 6 types of Brunnstrom levels is 32.24%. The results show that the actions selected in the last experiment can significantly improve the accuracy of patients' rehabilitation evaluation (p = 0.0035 < 0.05). From the perspective of the model, we can find that using the stacking ensemble learning model designed in this paper has the best accuracy of Brunnstrom level classification for most actions. Among them, the average accuracy of rehabilitation evaluation of the LDA model on nine kinds of rehabilitation training actions is 43.89%, and the average accuracy of the stacking ensemble model is 69.78%. This shows that the stacking ensemble model proposed in this article can significantly improve the accuracy of patient rehabilitation level assessment (p = 0.0172 < 0.05).

IV. SUMMARIZED AND PROSPECTED

Aiming at solving the problem that the rehabilitation level of stroke patients can’t be automatically evaluated in the process of home-based rehabilitation training, the paper proposes a method of Brunnstrom stage automatic evaluation for stroke patients by using multi-channel sEMG. This method first selects the suitable actions from nine kinds of rehabilitation training actions, and then constructs the rehabilitation evaluation model based on the ensemble learning method. In order to verify the effectiveness of the method proposed in this paper, the specially selected evaluation actions and stacking ensemble learning model were tested on the sEMG data of 24 patients. The experimental results show that the selected rehabilitation evaluation actions and stacking ensemble learning model can significantly improve the accuracy of patients' rehabilitation level evaluation. By using the method presented in this paper, patients can complete a rehabilitation assessment at any time and place by wearing sEMG sensors. At the same time, the method mentioned in this paper can also be integrated into the rehabilitation robot system to complete the rehabilitation evaluation while the patient is undergoing rehabilitation training, and the rehabilitation strategy can be dynamically adjusted according to the evaluation results, so as to further improve the rehabilitation efficiency of the patient.

However, the method proposed in this paper still has some limitations. Although the method proposed in this paper can improve the classification accuracy of 6 types of Brunnstrom stages to 94.36%, it has not been verified whether the algorithm is effective under some non-ideal conditions, such as electrode position deviation and sensor channel damage. Therefore, in the following work, we will focus on solving the problem of evaluation of patients' rehabilitation grade under non-ideal circumstances, so as to further promote the application of home-based rehabilitation training in practice.

REFERENCES


