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A Time-Series Augmentation Method Based on Empirical Mode Decomposition and Integrated LSTM Neural Network

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***Abstract*— Adequate patients' data have always been critical for disease assessment. However, large amounts of patient data are often difficult to collect, especially when patients are required to complete a series of assessment movements. For example, assessing the hand motor function of stroke patients or Parkinson's patients requires patients to complete a series of evaluation movements, and it is often difficult for patients to complete each group of actions multiple times, resulting in a small amount of data. To solve the problem of insufficient data quantity, this study proposes a data augmentation method based on empirical mode decomposition and integrated long short-term memory neural network (EMD-ILSTM). The method mainly consists of two parts: one is to decompose the raw signal by the method of EMD, and the other is to use LSTM for data augmentation of the decomposed signal. Then, the method is tested on the public dataset named Ninaweb, and the test results show that the classification accuracy can be improved by 5.2% by using the augmented data for classification tasks. Finally, clinical trials are conducted to verify that after dimensionality reduction, the augmented data and raw data have smaller intra-class distances and larger inter-class distances, indicating that data augmentation is effective.**

I. INTRODUCTION

In the era of deep learning, research in many fields has shown that the larger the dataset, the better the generalization performance of the model. When the task involves the analysis of biomedical signals, such as motion signals, electromyography signals, etc., more data can also help doctors better understand patients, so as to better diagnose the condition and formulate more accurate rehabilitation strategies. However, obtaining larger data sets is a complex task and can be an unpleasant experience for patients due to fatigue, patient limitations or physical impairment. Therefore, the lack of sufficient data makes analyzing these signals a challenging task.

Over the past few years, the topic of data augmentation has attracted many researchers. In the work of [1], the methods of jittering, scaling, rotating, permutating, magnitude-warping and time-warping were used to augment Parkinson's data recorded by accelerometer sensors, to assess the degree of Parkinson's disease. However, these methods are simple sequential operations, and the changed signal also loses its physical characteristics. Kamycki developed a suboptimal warped time-series generator for generating augmented data, and proved the effective of this method by the task of time-series classification [2]. However, it is not sufficient to prove the validity of augmented data only by classifying tasks. Haradal proposed generative adversarial networks (GAN) to enhance electrocardiogram and electroencephalography datasets [3]. In addition to data augmentation of physiological signals based on GAN [4], [5], LSTM was also used to augment motion signals for action classification [6]–[8]. Although these deep learning-based methods can use augmented signals to improve the task of action recognition, they require quantitative metrics to evaluate the augmented data. In this study, in addition to using quantitative metrics to evaluate the effectiveness of data augmentation, we also use two tasks to demonstrate the effectiveness of data augmentation. The first task is a gesture classification task, and the second task is PCA dimensionality reduction.

The main contributions of this work can be concluded as follows:

1) We propose a data augmentation method based on empirical mode decomposition and integrated long short-term memory neural network (EMD-ILSTM). In the method, the raw hand motor signals are decomposed by EMD, and then the decomposed signals are integrally augmented by LSTM, and then each channel signal is combined. Moreover, two metrics of similarity and difference are used to evaluate the augmented data.
2) The augmentation method is tested on the public dataset named Ninaweb, and the test results show that the classification accuracy can be improved by 5.2% than the benchmark classification results by using the augmented data for classification tasks.
3) Clinical trials are conducted to verify that the coordinate positions of the augmented data and the raw data after dimensionality reduction have the smaller intra-class distance and larger inter-class distance, which indicates that the data augmentation method is effective.

The remaining parts of this study are organized as follows: Section II introduces the method of EMD-ILSTM in detail. Section III exhibits the results of data augmentation and classification accuracy. Finally, Section IV discusses the results and concludes the paper.

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II. METHODOLOGY

The framework of the EMD-ILSTM is shown in Fig.1. First, the joint angle matrix (5m, assuming that the length of the data is m) of the finger is split into five one-dimensional signals (m), each signal representing the bending angle of a finger. Next, each angle signal is artificially decomposed into 7 groups of signals (7m) using EMD. Then the matrix (35m) of all decomposed signal concatenations is integrally input to one LSTM network. And the LSTM network outputs the augmented matrix (35m). Finally, the matrix is divided into 5 groups (7m) corresponding to 5 fingers in turn, and then the signals of each finger are summed to obtain one-dimensional data, and the data of the 5 fingers are concatenated into an augmented matrix (5m).

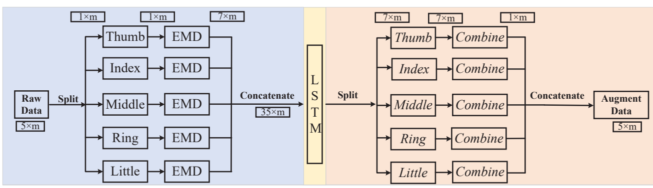

Fig. 1. The framework of the EMD-ILSTM.

A. Empirical Mode Decomposition

Empirical mode decomposition (EMD) can decompose the raw signal into intrinsic mode functions (IMF). The decomposition results in a set of empirical mode functions and a residual term, which can represent the trend of the signal or a fixed value [9]. The raw data will be decomposed as follows:

$$X(t) = \sum_{i=1}^{n} \mathrm{IMF}_i(t) + r_n(t), \qquad (1)$$

where $X(t)$ is raw data, $\mathrm{IMF}_i(t)$ are intrinsic mode functions and $r_n(t)$ is residue.

B. LSTM

The structure of the LSTM unit is shown in Fig. 2. It contains two LSTM layers, two fully connected layers (FC) and one regression layer (RE).

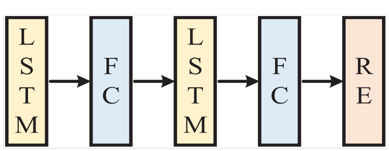

Fig. 2. The structure of the LSTM unit.

C. Ablation Experiment

The framework of the three ablation tests is shown in Fig. 3. Fig. 3 (a) indicates 5 LSTM units to augment the data of the bending angles of the 5 fingers respectively, Fig. 3 (b) shows only one LSTM unit to augment the data of the bending angles of all the 5 fingers, and in Fig. 3 (c) the motion curves of the 5 fingers are first decomposed by EMD, and then performed data augmentation by 5 LSTM units.

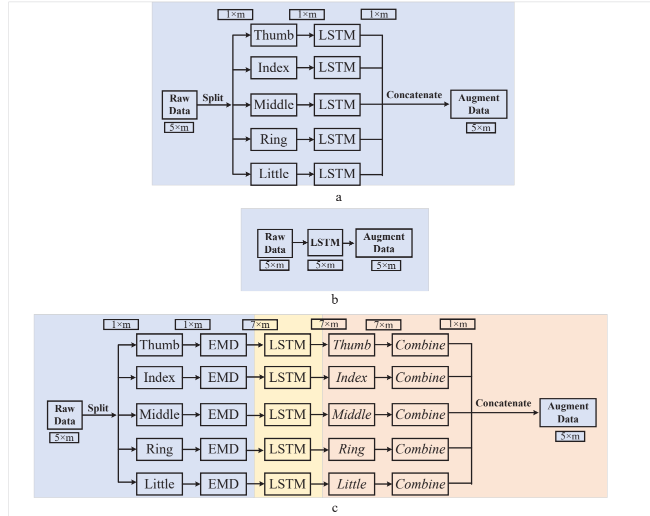

Fig. 3. The three frameworks of the ablation experiment.

D. Metrics

To compare the augmentation data effectively, the Spearman coefficient (SC) and the Pearson coefficient (PC) are used as the similarity metric, and the difference percentage (DP) is used as the difference metric. DP can be written as

$$DP = \sum_{i=1}^{45} \left(\left| \frac{DataRaw_i - DataAug_i}{DataRaw_i} \right| \right) \times 100\%, \qquad (2)$$

where $DataRaw$ and $DataAug$ are the features of length 45, consisting of mean value, root mean square, mean absolute value, average power, average amplitude change, standard deviation, ratio of difference of quartile and correlation matrix. The augmentation effect is better when the values of SC and PC are close to 1 and the value of DP is small.

In addition, to prove the validity of augmentation data, we use the framework proposed in this study to conduct data augmentation on DB1 of Ninaweb dataset [10], and add the augmentation data to the training set. Then we use the sliding windows to preprocess the data and the length of sliding window is 400 ms. The types of features we used are mean absolute value (MAV), variance (VAR), marginal discrete wavelet transform (mDWT), waveform length (WL) and histogram (HIST). The classification methods include k-nearest neighbors (k-NN), linear discriminant analysis (LDA), mutilayer perception (MLP), quadratic support vector machine (QSVM), and linear support vector machine (LSVM). Finally, we compare the classification results with the benchmark results of the dataset [11].

E. Clinical Trials

To apply the augmentation method of this study to clinical trials, we use leap motion to collect the data of 4 Parkinson's patients in the Chinese Research Rehabilitation Center. The patients perform 4 kinds of hand movements of the UPDRS scale, namely finger tapping, finger group flexion, pronation-supination movements of hands and postural tremor of the hands. Each movement is repeated 10 times. Then the raw data and augmented data of 4 patients are reduced to 2 dimensions using PCA, and the data of 4 subjects are plotted. This research was reviewed and approved by the Ethics Committee of the China Rehabilitation Research Center (approval number: 2021-108-1). Each subject signed a written informed consent prior to enrollment.

III. Results

A. EMD

Figure 4 exhibits the EMD decomposition curves, the blue one is the raw curve, the last red curve is the residue, and the remaining red ones are the decomposed IMF. There are 6 IMF and 1 residue signals.

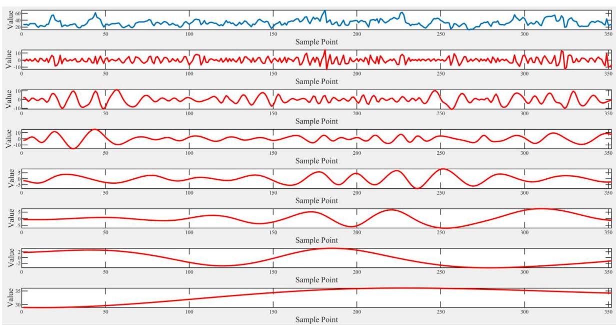

Fig. 4. The raw signal and its EMD signals.

B. LSTM

In this study, the first 50% of the data are used for training and the last 50% for testing. At each time step of the input sequence, the LSTM network learns to predict the value of the next time step. When training the signals decomposed by EMD, the training set is copied 5 times and connected before training. More detailed parameters of the training process are shown in Tab. I.

TABLE I: PARAMETERS OF LSTM

Parameter	Value
Solver	Adam
MaxEpochs	300
InitialLearnRate	0.005
LearnRateDropPeriod	100
LearnRateDropFactor	0.2
numHiddenUnits	200

C. Data augmentation results

The results of augmentation under four different frameworks are shown in Fig. 5. Fig. 5 (a)-(c) correspond to the three frameworks in Fig. 3, respectively, and Fig. 5 (d) is the augmentation result based on EMD-ILSTM. A more detailed comparison is shown in Tab. II. The red text in Tab. II indicates that the augmentation effect in Fig. 5 (d) is the best, and the raw curve is basically restored.

TABLE II: COMPARISON OF DATA AUGMENTATION EFFECTS OF FOUR FRAMEWORKS

Framework	Spearman	Pearson	DP
a	0.9325	0.9923	16.9
b	0.9937	0.9929	6.78
c	0.9410	0.9954	12.6
d	0.9948	0.9994	4.15

D. Classification Result

In Fig. 6, the left column of the same color represents the classification accuracy before data augmentation, and the right column represents the classification accuracy of the data after augmentation. The classification accuracy of training with additional augmented data is higher than the benchmark classification results. After calculation, the average classification accuracy is improved by 5.2%.

E. Clinical Trails

Figure 7 shows the snapshot of the experiment. The patient places his hand 30 cm above the leap motion and completes 4 hand movements of the UPDRS scale. We collect the data from the patients and augment the data by the method proposed by this study. Then these data are extracted to form features with length 45, and the coordinate positions of the features after PCA (default parameters in MATLAB) are shown in Fig. 8. Four different colored dots represent 4 subjects with different degrees of disease. Circles and five-pointed stars represent raw data and augmented data, respectively. It can be seen that the augmented data is very close to the raw data, and farther from other patients' data points, indicating that the augmentation data is effective.

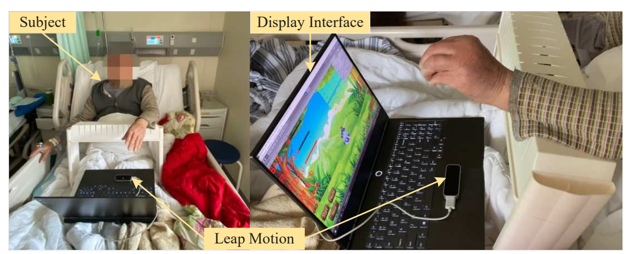

Fig. 7. The clinical trail.

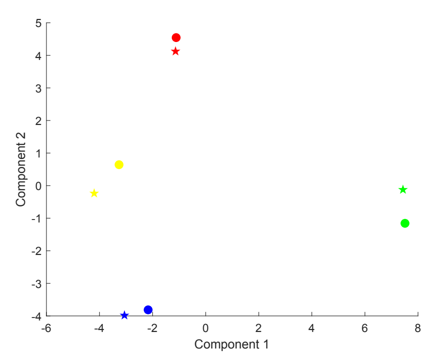

Fig. 8. Data distribution of four subjects after PCA.

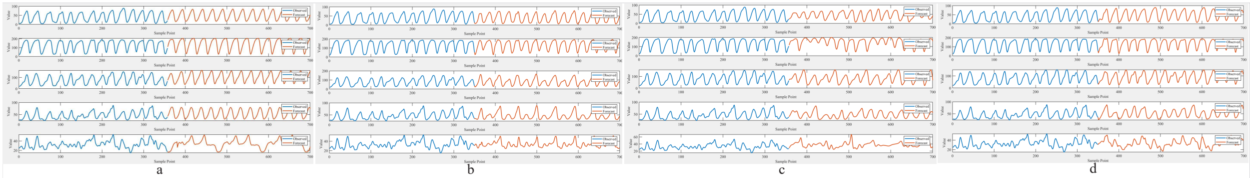

Fig. 5. The results of augmentation under four different frameworks.

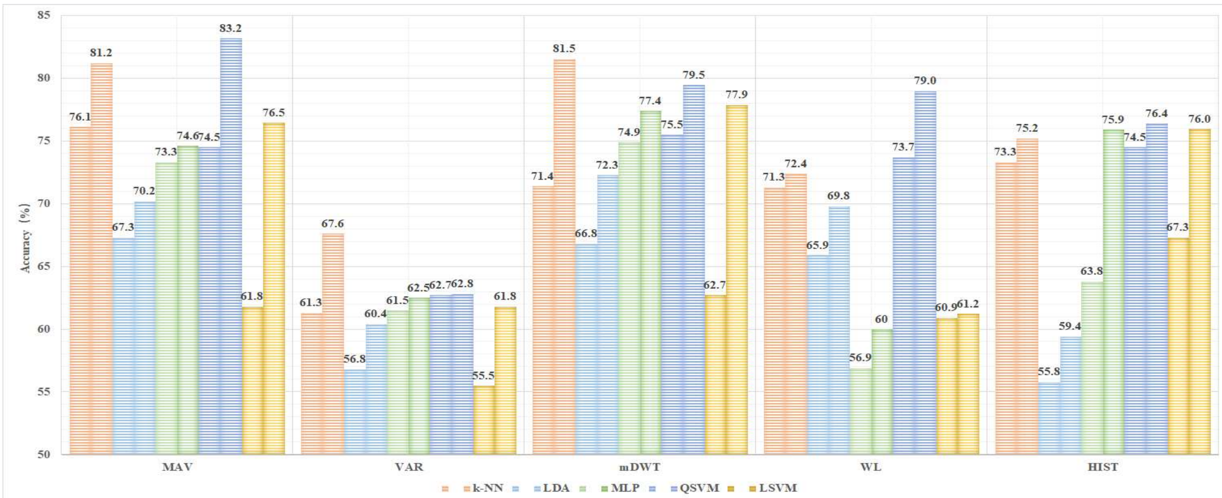

Fig. 6. The accuracy of the classification.

IV. Discussion and Conclusion

As can be seen from Fig. 4, EMD decomposes complex signals into simple multi-channel signals. The data augmentation effect of these simple signals is better than that shown in Fig. 5(a), as exhibited in Fig. 5(c). By integrally inputting the motion data of all fingers into one LSTM unit for training, the neural network can find the motion rules of 5 fingers on the whole, so the augmented data is closer to the original data, as shown in Fig. 5(b). Combining the advantages of EMD and integrated LSTM, the proposed EMD-ILSTM method works best, as shown in Fig. 5(d).

This study proposes a data augmentation method called EMD-ILSTM, which can augment time-series signals efficiently. We use the method to perform a classification test on DB1 of the Ninaweb dataset, and the results show that additionally using the augmented data for classification, under the same feature and classification method, the classification accuracy is 5.2% higher than the benchmark classification results. In addition, the results of clinical trials also show that the augmented data has smaller intra-class distance and larger inter-class distance, which indicates that our proposed data augmentation method is effective.

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