Task II

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**EMG signal test report**

Electromyography (EMG), the use of electronic instruments to record electrical activity when muscles are still or contracted, and the use of electrical stimulation to examine nerve, muscle excitation and conduction functions. English referred to as EMG. Through this examination, the functional status of peripheral nerves, neurons, neuromuscular junctions, and muscles themselves can be determined. The purpose of this experiment is to classify the acquired EMG signals, including collecting data, forming data sets and test sets, and model training.

First of all, for the data acquisition part, the signal generated by the precise action is more convenient to classify. We specify the action mode of the acquisition. Before the official acquisition starts, set the save time according to the selected number of acquisition actions. If 10 sets of actions need to be collected, set to 100000. (100s), if 8 sets of actions are collected, set 80000 (80s). Each set of actions takes up 10 s. Here we have 5 sets of actions:

0-5s: rest, keep hands relaxed

6-10s: Action 1

11-15s: rest, keep hands relaxed

16-20s: Action 2

21-25s: rest, keep hands relaxed

26-30s: Action 3

31-35s: Rest, keep hands relaxed

36-40s: Action 4

41-45s: rest, keep hands relaxed

46-50s: Action 5

51-55s: Rest, keep hands relaxed

Second, read the acquired signal and form a training set and test set in a ratio of 7:3. The code is shown in Figure 1.

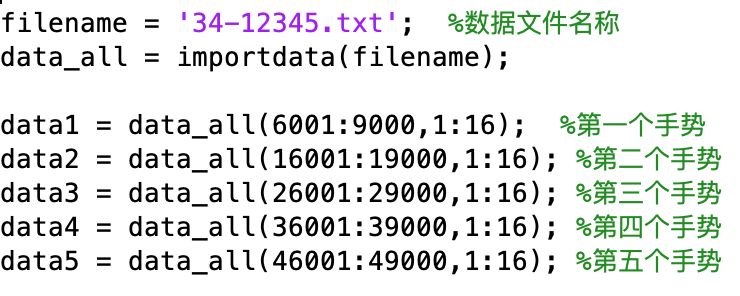


Figure 1-a Data read

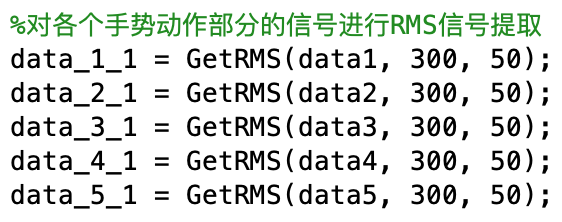


Figure 1-b Extracting the RMS signal

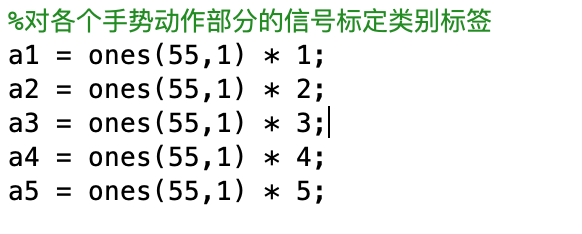


Figure 1-c Calibration Label

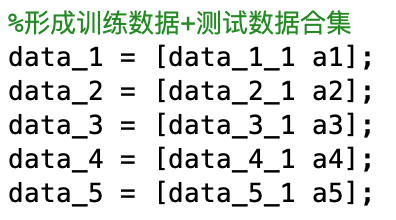


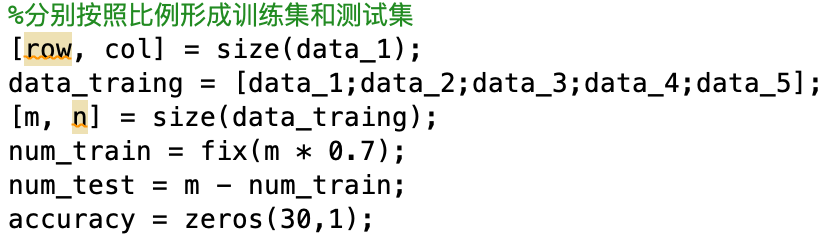
Figure 1-d Forming training data + test training collection

Figure 1-e Forming a training set and test set

The RMS signal extraction part of the code is shown in Figure 2.

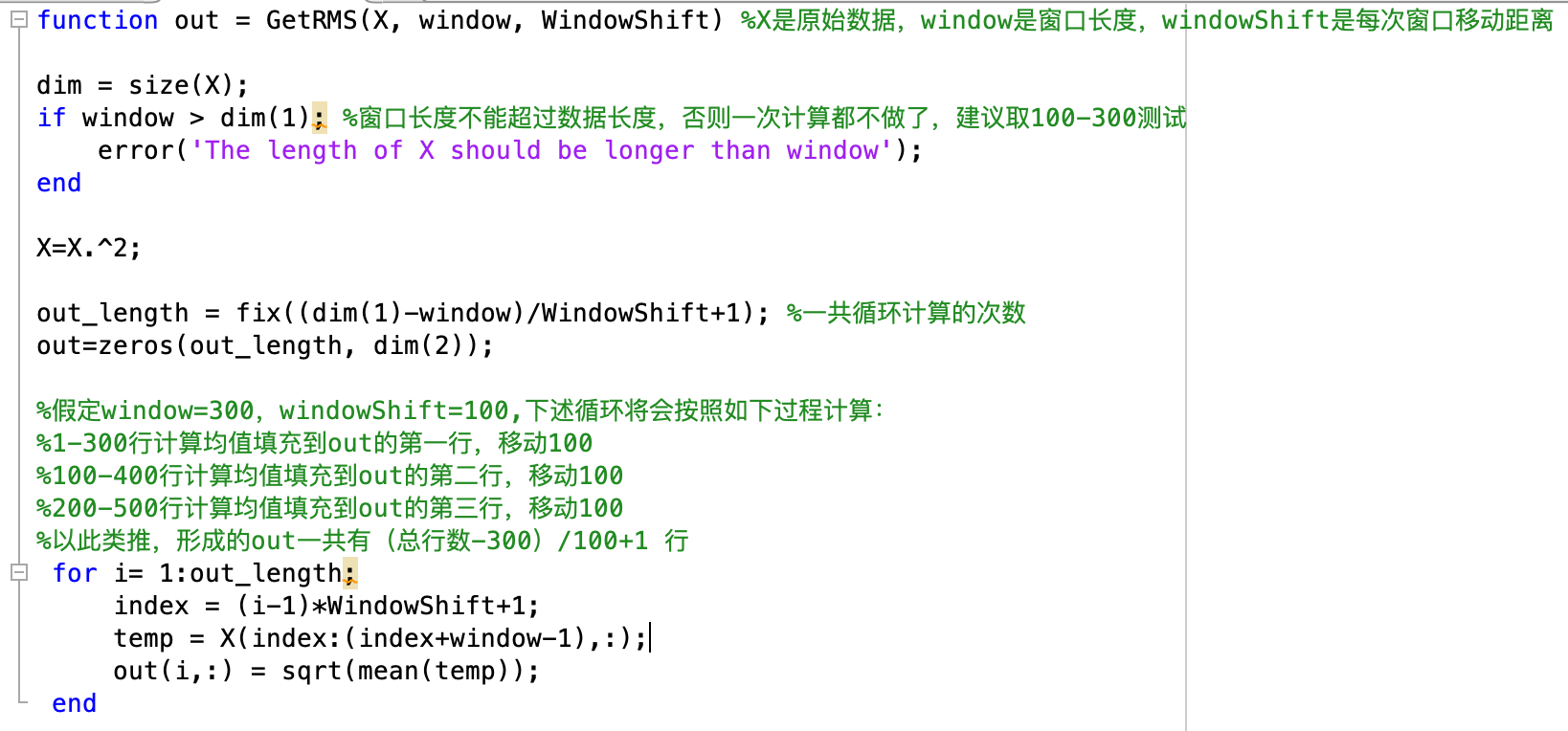


Figure 2 RMS signal extraction

We use a total of four classification methods to classify, the code of the key algorithm is shown in Figure 3.

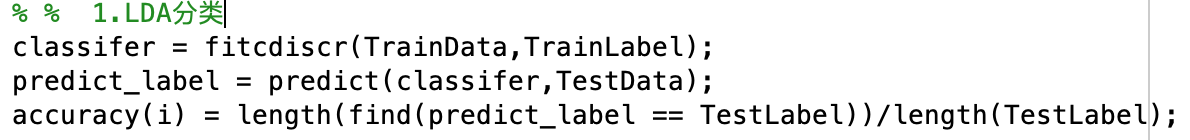


Figure 3-a LDA classification algorithm

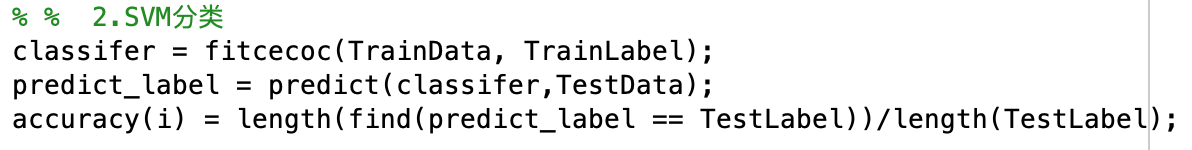


Figure 3-b SVM classification algorithm

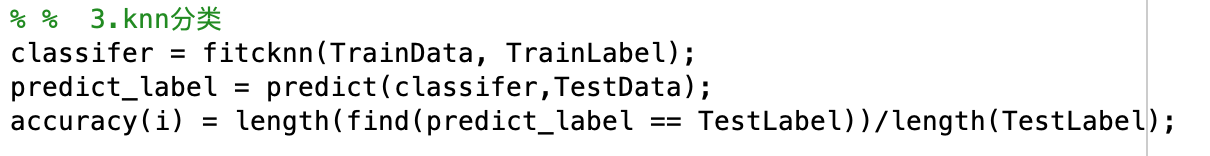


Figure 3-c KNN classification algorithm

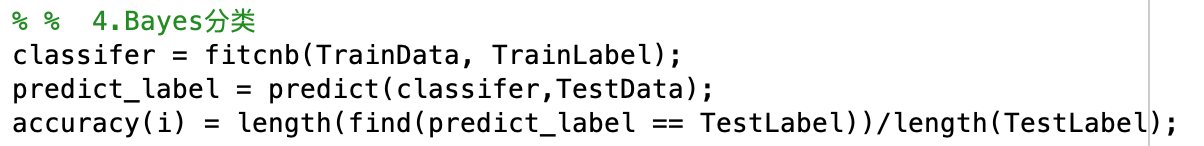


Figure 3-d Bayes classification algorithm

We compared the running time and accuracy of the four algorithms LDA, SVM, KNN, and Bayes. We found that SVM iterations were the slowest and KNNs were the fastest. In terms of accuracy, the accuracy of SVM is better than the other three algorithms. The accuracy of the Bayes algorithm is as low as 57%, which we did not expect. Maybe we have a problem when implementing the algorithm. As shown in Figure 4, it is the result of our comparison.

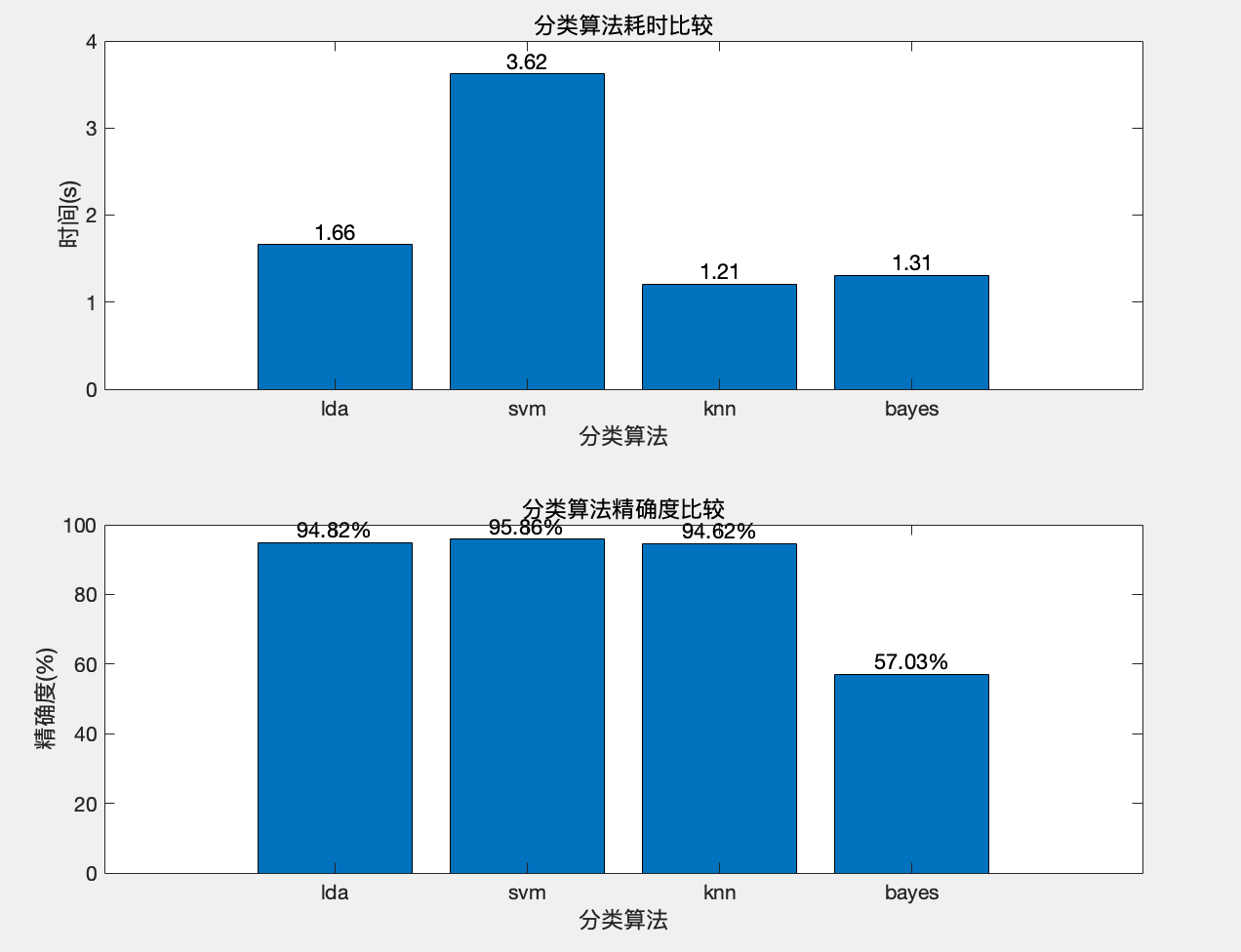


Figure 4 the result of our comparison

We have found that each classification method can achieve higher precision and each has its own advantages. We have an in-depth understanding of the LDA algorithm. Here are our insights.

LDA (sexual discrimination analysis) adopts a supervised method. It first reduces the dimension of the training data and then finds a linear discriminant function. The basic idea is to project the high-dimensional model samples into the optimal discriminant vector space. The effect of extracting the classification information and compressing the feature space dimension is achieved. After the projection, the model sample has the largest inter-class distance and the smallest intra-class distance in the new subspace, that is, the model has the best separability in the space. Therefore, it is an effective feature extraction method. Using this method, the inter-class divergence matrix of the model samples after projection can be maximized, and at the same time, the intra-class divergence matrix is the smallest. That is to say, it can ensure that the model samples have the smallest intra-class distance and the largest inter-class distance in the new space after projection, that is, the mode has the best separability in the space.

First, give N examples of features d-dimensional, , where There are samples belonging to the category , and the other samples belong to the category . Now we feel that there are too many original features, we want to reduce the d-dimensional features to only one dimension, and we must ensure that the categories can be "clearly" reflected in low-dimensional data, that is, this dimension can determine each sample. category. Assuming that the best mapping vector is w (d dimension), the projection of the example x (d dimension) to w can be expressed by equation (1).

（1）

Suppose the sample vectorcontains 2 eigenvalues (d=2), we Just look for a line (direction w) to make the projection, and then find the line that best separates the sample points.

The next step is to find the best w from a quantitative perspective.

First, the mean points before and after projection of each type of sample are (where the total number of samples is C=2), and Ni represents the number of samples per class:

（2）

（3）

It can be seen from equations (2) and (3) that the mean after projection is also the projection of the center point of the sample.

Secondly, it is possible to make the two types of sample mean points after projection as far apart as possible, which may be the best projection vector.

（4）

In addition, you need to add a constraint-hash value, that is, to find the hash value of the projected class, as in equation (5):

（5）

It can be seen from the formula that the geometric value of the hash value is the degree of density of the sample points. The larger the value, the more dispersed, and vice versa. The sample points after the projection we want are: the more separate the sample points of different categories, the better the aggregation of the same kind, that is, the larger the distance between the mean points, the better the hash value. The smaller the hash value, the better. Just right, we can use J(w) and S(w) to measure. Therefore, the final metric formula can be defined as Equation (6):

（6）

We just need to find the w that makes J(w) the biggest.

However, this method also has certain defects. For example, it is not suitable for dimension reduction of non-Gaussian samples, and the effect is not good enough when the sample classification information depends on the variance rather than the mean. Of course, the data may be over-fitting.