

# Research On human motion recognition algorithm based on WLD

SUN Qiu Feng, LI Xia

Nanjing Normal University Taizhou College , Jiangsu, 225300 , China

**Abstract:** With the rapid development of intelligent technology, People's lives have gradually entered the era of information and intelligence. Wearable devices are becoming more and more popular, it is easier to use sensors to obtain data, even physiological data, from human body. When large amounts of data are collected by sensors, we can analyze and model them. The values of each characteristic are used to judge the user's state, then according to the state we can provide users with more accurate and convenient services. In this paper, the data collected by different sensors are used to establish a prediction model and analyze the comparative effect of different recognition algorithms on the test data. The results of the experiment shows that the Bayesian method based on WLD identifies the state of the human body better.

**Keywords:** motion status; WLD; sensor

## 1 Introduction

With the widespread use of intelligent wearables, a large amount of data in human motion monitoring can be trained and learned to build predictive models, then provide accurate status tips for special populations, such as by predicting status, to reduce the damage caused by falls among the elders. In this paper, a variety of classification algorithms are used to model and predict the motion state, and finally implement the low equipment requirements and high-accuracy detections of human body motion state.

## 2 Feature data

Each user dataset used in algorithmic analysis contains a feature file and a label file. Each line in the feature file corresponds to all sensor values at a time, and each line in the label file records the made user's posture for the corresponding moment in the feature file. Features of the feature file, shown in Table 1 below:

**Table 1. Feature properties**

1	2	3-15	16-28	29-41
Timestamp	Heart rate	Sensor 1	Sensor 2	Sensor 3

The corresponding 13 columns of data characteristics in sensor 1 contain: 1 temperature data, 3 one-type three-axis acceleration data, 3 two-type three-axis acceleration data, 3 three-axis gyroscope data and 3 three-axis magnetic field data, shown in Table 2 below:

**Table 2. Some sensor types**

3	4-6	7-9	10-12	13-15
temperature	one-type three-axis acceleration	two-type three-axis acceleration	三轴陀螺仪	三轴磁场

The body's temperature data can reflect the intensity of current activity, generally at rest, the body temperature tends to stabilize at 36.5°C, when the temperature is higher than 37°C, may be a short period of intense exercise, such as running and cycling.

There are two types of acceleration sensors in the data, which can guarantee the integrity and accuracy of the data by mutually corroborating them. Through the three values corresponding to the acceleration sensor, we can know the corresponding acceleration on the three axes x, y, z in space, and the acceleration in space is closely related to the user's posture, for example, when the user jumps up, the acceleration on the z-axis will surge<sup>[1]</sup>.

Gyroscopes are commonly used for angle motion detection and can determine whether the body angle is horizontal, tilted or vertical when the user wears the sensor<sup>[2]</sup>.

Magnetic field sensors can detect the strength and numerical size of the magnetic field around the user, which can help to understand the user's environment. For example, in an office, the magnetic field near the user's seat is largely fixed, and when the magnetic field changes, it can be inferred that the user's location and scene have changed.

Label files serve as standard reference guidelines for training sets, and each line in the label file represents a user's posture category that corresponds to the corresponding rows in the feature file. There are 25 kinds of physical postures, such as, inactivity, sitting, running etc<sup>[3-4]</sup>.

### 3 WLD

For two given strings (or sequences):  $a$  and  $b$ , there are three string-to-string correction operations: (1) Single symbol deletion:  $a = c \ x \ d$ ,  $b = cd$ , which means that the symbol  $x$  between  $c$  and  $d$  is deleted; (2) Single symbol insertion:  $a = cd$ ,  $b = c \ x \ d$ , which means that the symbol  $x$  is inserted between  $c$  and  $d$ ; (3) Single symbol substitution:  $a = c \ x \ d$ ,  $b = c \ y \ d$ , which means that the symbol  $x$  is replaced by the symbol  $y$ . Here  $c, d \in \Sigma^*$  denote two sub-strings,  $x, y \in \Sigma^*$  denote two different symbols (i.e.,  $x \neq y$ ).

If one of rules above holds true, the string  $a$  can be transformed into the string  $b$  in one step correction. The Levenshtein distance (or edit distance) is defined as the smallest number of correction operations converting the string  $a$  into the string  $b$ .

Since in many applications three correction operations indicate different meanings, it is necessary to determine different weights for the different rules. In this case, the weighted Levenshtein distances (or WLD) was introduced, which is defined as the minimum total weight of single symbol insertions, deletion and substitutions required to convert one string into the other. If the weight of insertion is equal to that of deletion, WLD still satisfies the distance definition in functional analysis.

Let  $a_i$  and  $b_j$  be two substrings from the first  $i$  and  $j$  symbols of  $a$  and  $b$  respectively. WLD between them, i.e.,  $d_{i,j}$ , can be calculated as follows,

$$\begin{aligned} d_{0,0} &= 0, \\ d_{i,0} &= d_{i-1,0} + w^D, \\ d_{0,j} &= d_{0,j-1} + w^I, \\ d_{i,j} &= \min(d_{i-1,j} + w^I, d_{i-1,j-1} + w^S, d_{i,j-1} + w^D), \\ i &= 1, \dots, |a|, j = 1, \dots, |b|, \end{aligned}$$

where  $w^I$ ,  $w^D$  and  $w^S$  denote different weights for insertion, deletion and substitution operations, and  $|a|$  and  $|b|$  the lengths of two strings. In this case, WLD of two strings  $a$  and  $b$  is  $d_{|a|,|b|}$ , which is used to replace Euclidean distance between two vectors.

Fig.1 illustrates the computational procedure about WLD, where each path from (0,0) to  $(|a|,|b|)$  (e.g., the solid line in Fig.1) corresponds to a sequence of corrections converting  $a = A C G C$  into  $b = A C G T$ . WLD is the optimal path minimizing the total weight summation (the dotted line in Fig 1).

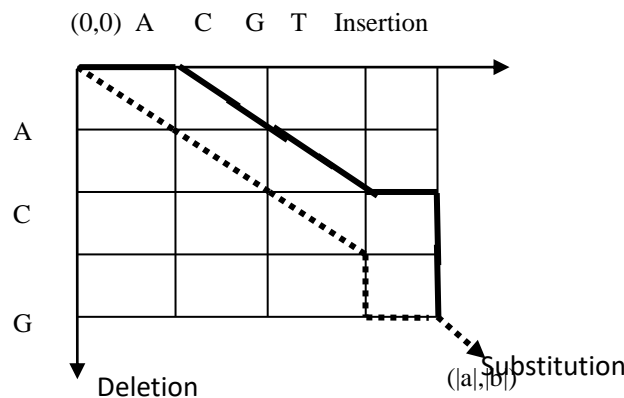


Fig 1. The Computational Procedure of WLD

In order to eliminate the impact of string length and handle the application problems effectively in numerical computation, it is necessary to convert WLD into the interval between 0 and 1. In our experiment below, we define weights of both insertion and

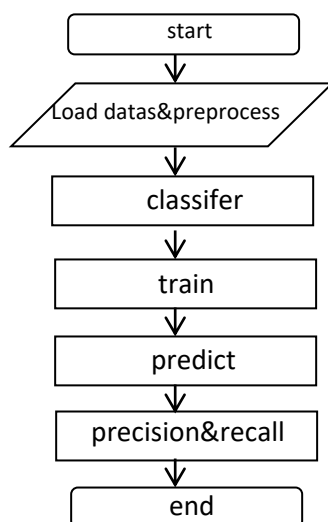
deletion operations as 1. For the substitution operation, if two symbols are identical, the weight is equal to 0 ; otherwise the weight equals 3. Thus WLD varies from 0 to  $|a| + |b|$  (i.e. the length summation of two strings). The original WLD can be simply divided by  $(|a| + |b|)$  to convert its value into the range from 0 to 1.

#### 4 Algorithmic process and result analysis

(1) Loading all the data into memory from feature files and label files, some values are missed, if these features are fed into subsequent calculations without processing, may result in a decrease in model accuracy and increase the amount of computation, the use of averages in this article to complement the missing data.

(2) Create a corresponding classifier and train data input,divide the data into 5 parts,the first 4 as training data,and the last 1 as test data,then create a prediction model,the code is as follows:

(3) Use the model to predict the test data and evaluate the model by comparing real and predicted values.The algorithm flowchart is shown in Fig 2 below:



**Fig 2. The algorithm flowchart**

From the above analysis,we can get the comparison results of three kinds of recognition algorithms in three dimensions:precision,recall and f1-score,which are shown in Table 3 below:

**Table 3. A comparison of the results of 3 kinds of algorithms**

Algorithm	KNN	DT	GNB	Bayesian based on WLD
precision	0.69	0.61	0.74	0.89
recall	0.69	0.64	0.68	0.82
F1-score	0.68	0.60	0.68	0.81

As shown in Table 3,Bayesian classifier based on WLD words best in term of precision,in terms of recall and f1-score,KNN perform best.Overall,Byesian classifier and KNN work better than DT.

#### 5 Conclusion

The motion information collected by different sensors taken are used as the data source to explore the recognition effect of different recognition methods on the motion state of human body.

Combined with three recognition algorithms,the sensor feature values extracted are used as input in the recognition system,and a prediction model is established to realize the prediction of the human body's motion state.Model learning is carried out by using training data,and the corresponding classification is given to the test samples,then comes out the prediction of different human states by three algorithms.By comparing the precision and recall of the three algorithms,we can get that the prediction effect of Bayesian algorithm based on WLD is better.

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