

# Identification of Motion Conditions Based on Self-organizing Competitive Neural Network Algorithm

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**Abstract.** Against the false alarms and false negatives caused by the error of alarm threshold selection because different working conditions when the early warning device is close to the same charged body, this paper proposes self-organizing competitive neural network model for Identification working conditions of worker, which climbing towers, climbing slopes and horizontal walking. Firstly, acceleration sensors and barometric pressure sensors are used to collect the acceleration value and barometric data of the head during the exercise of the experimenter. Secondly, Multi-source information collaborative filtering processes data to obtain effective relative height values and obtain fitting parameters by first-order fitting. Finally, building self-organizing competitive neural network model based on parameters. This paper selects outdoor towers, slopes with a slope of about 30° and horizontal roads as experimental platforms and collect 400 sets of data for each platform. Then randomly select 900 sets of data for training, 300 sets of data for verification. The experimental results show that the accuracy of the training sample reaches 94.67%, and the accuracy of the test sample reaches 92.73%, which meets the requirements for working condition identification in the outdoor environment.

## 1. Introduction

With the development of social science and technology, the measurement and research on stealth information such as electric field strength and voltage level under the complex power operation environment are continuously strengthened. At present, there are few researches on the identification of working conditions when the power workers are close to the electrified body, such as horizontal proximity, climbing slope and climbing tower approach, resulting in the accuracy of voltage level identification being affected <sup>[1]</sup>. In order to improve the recognition accuracy of voltage level, this paper studies the identification of three working conditions such as horizontal approach, climbing slope and climbing tower approach the tower. At present, the methods of working condition identification mainly include image recognition and inertial identification. On the one hand, Image recognition is susceptible to obstacles, inconvenience to carry, and high cost. The inertial recognition uses the acceleration sensor to measure the movement of the operator under different working conditions. Identify different motion conditions by the acceleration amplitude <sup>[2]</sup>. However, this



method has a large error in the measurement process and is susceptible to additional actions by the operator, resulting in a high false positive rate.

Based on the above problems, this paper proposes identification model of motion conditions based on self-organizing competitive neural network algorithm [3]. The acceleration sensor and pressure sensor are installed on the head of the operator to collect total acceleration values and barometric pressure values during operation of the operator's head. The three-axis acceleration value and the air pressure value are converted into the combined acceleration value and the relative height value by the acceleration synthesis formula and the height conversion formula of the starting point of the operator. Using multi-source information collaborative filtering [4] method to collaboratively filter acceleration values and relative altitude values to extract effective relative height values. First-order fitting of effective relative height values is used to obtain fitting parameters [5]. Finally, the fitting parameters are used as input to establish a self-organizing competitive neural network model for classification and identification of three working conditions [6-7]. The method has the advantages of easy carrying, low cost, high recognition accuracy, etc. It can not only improve the accuracy of related information measurement in power operations, but also has a wide application market.

## 2. Movement condition recognition system

This paper establishes a model for the identification of movement conditions, including three aspects: feature data collection, feature parameter extraction, and movement condition identification [8]. The identification system model is shown in Figure 1. The principle is to install the air pressure sensor and the acceleration sensor on the head of the operator first. The air pressure sensor collects the local air pressure value, and the acceleration sensor collects the three-axis acceleration value of the internal coordinates. Then, the data of the acceleration value and the air pressure value are pre-processed to obtain the combined acceleration and the relative height value relative to the starting point of the operator [9]. Using the multi-source information collaborative filtering method to extract the effective relative height value, the first-order fitting of the effective height value to extract the fitting parameters. Finally, using the fitting parameters as input, a self-organizing competitive neural network algorithm was established to train the fitting parameters and the self-organizing competitive neural network algorithm model was determined.

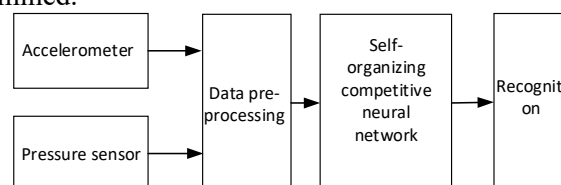


Figure 1. Model of motion condition recognition system

## 3. Data pre-processing

A reliable data pre-processing is the key to pattern recognition. The acceleration sensor selected in this paper is MPU6050 [10] and the pressure sensor is MS5611. Both sensors are high-precision and high-sensitivity sensors with a large amount of noise in the collected data. At the same time, the pressure value collected by the air pressure sensor is prone to drift in the static process, resulting in that the sensor directly measured data is not suitable for direct use. In this paper, the multi-source information collaborative filtering method is used to extract the effective relative height value. Finally, the first-order fitting of the effective relative height value is performed to obtain the fitting parameters. The overall structure is shown in Figure 2.

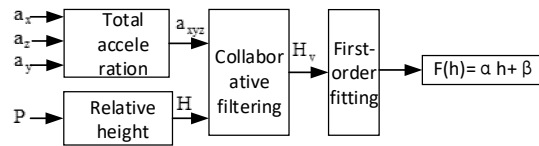


Figure 2. Data pre-processing structure

### 3.1. Data conversion

This article uses sensor to measure the three-axis acceleration during the movement of the operator <sup>[11]</sup>. The measured internal coordinate system accelerations on the X-axis, Y-axis, and Z-axis are expressed as  $a_x$ 、 $a_y$ 、 $a_z$ ，When the installation angle of the accelerometer is inconsistent, the collected data of  $a_x$ 、 $a_y$ 、 $a_z$  are affected. In order to solve this problem, this paper synthesizes the total acceleration values  $a_x$ 、 $a_y$  and  $a_z$  in the internal coordinate system into the resultant acceleration  $a_{xyz}$ . As shown in formula (2-1), using the air pressure sensor to measure the air pressure value under the working environment of the operator <sup>[12]</sup>. According to the formula (2-2) to (2-4), the measured pressure value is converted into the relative height value relative to the starting point of the power workers.

$$a_{xyz} = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (2-1)$$

$$H_1 = 44330 * [1 - (\frac{P}{P_0})^{1/5255}] \quad (2-2)$$

$$\text{Average\_H} = \frac{\sum_{i=1}^N H_1(i)}{N} \quad (2-3)$$

$$H = H_1 - \text{Average\_H} \quad (2-4)$$

Among them,  $P_0$  in the formula (2-2) is the standard atmospheric pressure value,  $P$  is the air pressure value collected by the air pressure sensor, and  $H_1$  is the altitude value corresponding to the air pressure value  $P$ . In formula (2-3),  $\text{Average\_H}$  is the average value of the first  $N$  altitude values at the starting position, and  $H$  in formula (2-4) is the relative height value of the relative starting position during the movement of the worker.

### 3.2. Multi-source information collaborative filtering

When the altitude of the relative initial position changes during the movement of the operator, the air pressure value converted into effective relative height value by conversion formula, this value can better reflect the height variation of power workers moving. When the operator is at a standstill, there are some reasons that cause a large error in the relative height value after the conversion, such as the shaking of the worker's body, the wind in the natural environment, the temperature change. So the value can't accurately reflect the height change of the relative initial position during the operation of the operator. The acceleration sensor can better identify whether the operator is in motion. When the operator is at a standstill, the amount of change in the acceleration amplitude collected by the acceleration sensor is small. When the operator is in motion, the amount of change in the acceleration amplitude collected by the acceleration sensor is large. According to the data characteristics collected by the air pressure sensor and the acceleration sensor during the motion, this paper adopts multi-source information cooperative filtering to extract the effective relative height value. An acceleration threshold  $A$  is set. When the amplitude of the combined acceleration value collected by the acceleration sensor is greater than the threshold  $A$ , the relative height value  $H$  after the air pressure sensor acquires the pressure value  $P$  is valid, otherwise it is invalid.

### 3.2.1 Acceleration threshold setting

The valid information is easy ignored when the speed threshold A is set too large. Of course, the acceleration threshold is set too small, some invalid information is easily mistaken for effective information. So, it is a key that a reasonable threshold set. In this paper, through the design experiment, the acceleration sensor and the air pressure sensor are installed on the top of the experimenter. The experimenter moves for a period of time, at rest for a period of time, collects ten sets of data, and calculates the average of the combined acceleration values of the stationary process and the motion process in each set of data. The value, and then the average value of the difference between the measured value and the arithmetic mean  $\gamma$ . Its  $\gamma$  calculation formula is shown as (2-5) to (2-6);

$$\text{Average1} = \frac{\sum_{t=1}^N a_t}{N} \quad (2-5)$$

$$\gamma = \frac{\sum_{t=1}^N (a_t - \text{Average})}{N} \quad (2-6)$$

In formula (2-5),  $a_t$  is the acceleration measurement value, N is the number of measurements per group; According to formulas (2-5) and (2-6),  $\gamma$  statistics are calculated as shown in Table 1.

Table 1.  $\gamma$  value in motion and static state

Number	$\gamma$ in motion	$\gamma$ in the stationary state
1	2055.677	297.3636
2	1270.684	180.6593
3	1654.277	161.4952
4	1220.836	152.1434
5	1309.186	242.0035
6	1723.971	169.1638
7	1749.586	214.5962
8	1438.46	165.0785
9	1838.586	163.0768
10	1257.057	126.2032
Average	1551.832	187.1784

It can be seen from Table 1 that the average value of the  $\gamma$  value during the ten groups of movement is 1551.832, and the  $\gamma$  at the static state is 187.1784. Therefore, the acceleration threshold A is set to be the median value of the two averages of 869.5.

### 3.2.2 Effective relative height extraction

Design electric power staff mobile with accelerometers and barometers on slopes with a gradient of approximately 30°. The operator walks for a period of time and stops for a period of time. In the process, the accelerometer and the barometer collect ten times of data as a group. And calculating the combined acceleration in the set of data using equation (2-1). At the same time calculate the acceleration threshold  $\gamma$  value using formulae (2-5) to (2-6). When  $a > b$ , the height change H of the relative starting position during the movement is valid, otherwise it is invalid; through this method, the effective relative height value is extracted, and the curve diagram of the effective relative height value is shown in Fig. 3

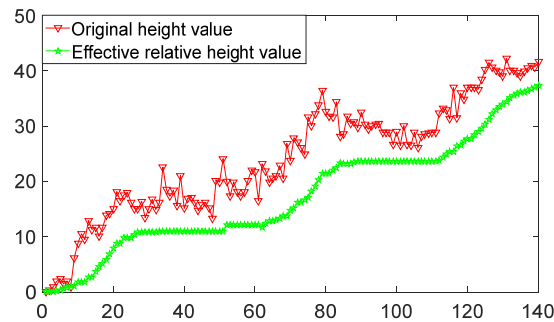


Figure 3. Effective relative height curve

It can be seen from Fig. 3 that the red curve is the original relative height value, and the green curve is the effective relative height value after the cooperative filtering. Using the acceleration value and the altitude value to coordinate the filtering, the noise fluctuation of the altitude value during the data acquisition process can be eliminated, and reaping smoother curve. Therefore, the collaborative filter method is used to deal with the changes in the effective relative height of the movement of the workers' levels, slopes, and towers under three different operating conditions. The processed change curve is shown in Figure 4

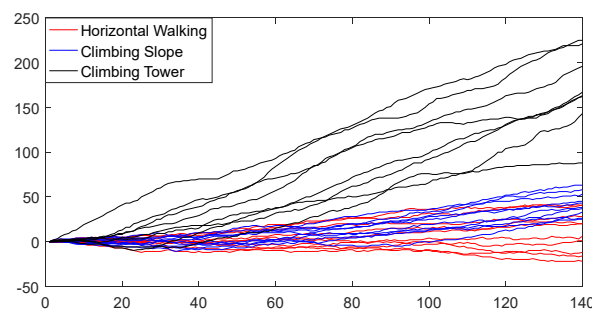


Figure 4. Effective relative height change curve under different working conditions

### 3.3. Data Fitting

It can be clearly seen from Fig. 4 that the effective relative height values of the workers under different working conditions of climbing tower, climbing slope and horizontal walking are different, and the variation curve approximates a quadratic equation curve, so the effective relative height value First-order fit of the curve. Let the fitting function be  $f(h) = \alpha h + \beta$ , Select an outdoor tower security zone, slope with an outdoor slope of approximately  $30^\circ$ , and horizontal road surface as the experimental platform. Collect 400 sets of data for each operating condition. The total number of data sets is 1200 sets, and the effective relative heights of 1200 data are respectively performed. First-order fitting, obtaining fitting parameters  $\alpha$  and  $\beta$ ; A self-organizing competitive neural network model was established. 300 sets of fitting parameters  $\alpha$  and  $\beta$  were randomly selected as training input and each of the other fitting parameters was used as a test for each working condition.

## 4. Self-organizing competitive neural network algorithm

### 4.1. Self-organizing competitive neural network model

The self-organizing competitive neural network model adopts the competitive learning idea, and the network output neurons compete with each other, and only one output neuron wins at the same time. Let the input value be a fitting parameter, as shown in equation (3-1)

$$X = \begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_n \\ \beta_1 & \beta_2 & \cdots & \beta_n \end{bmatrix} \quad (3-1)$$

Among them,  $\alpha_i$  and  $\beta_i$  ( $i \in (1, n)$ ) are the fitting parameters after data pre-processing, and the input  $X$  is normalized to obtain  $X'$ ; because the model recognizes three types of different working conditions, the weight  $W$  matrix is set to three rows and two columns. The indication is as shown in (3-2);

$$W = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \\ w_{31} & w_{32} \end{bmatrix} \quad (3-2)$$

Let the output value be  $Y$ , and its expression is as shown in (3-3):

$$OUT = \begin{bmatrix} out_{11} & out_{12} & \cdots & out_{1n} \\ out_{21} & out_{22} & \cdots & out_{2n} \\ out_{31} & out_{32} & \cdots & out_{3n} \end{bmatrix} \quad (3-3)$$

And, after calculating the output value  $OUT$ , the row of the maximum value is obtained for each column of the output matrix, so that the final output value is  $Y$ , and the expression is as shown in (3-4);

$$Y = \max(OUT) \quad (3-4)$$

Let the expression of the expected value  $M$  be as shown in (3-5):

$$M = [m_1 \quad m_2 \quad \cdots \quad m_n] \quad (3-5)$$

The error value is  $E$ , and the expression is as shown in (3-6):

$$E = M - Y \quad (3-6)$$

When the error value does not meet the requirement, the weight  $W$  needs to be updated. So normalized set of input data  $XR = \begin{bmatrix} \alpha'_i \\ \beta'_i \end{bmatrix}$  is randomly selected, and the output  $n.w$  obtained by multiplying the input with the weight is obtained, and the expression is as follows (3-7) shown.

$$n.w = \begin{bmatrix} nw_1 \\ nw_2 \\ nw_3 \end{bmatrix} \quad (3-7)$$

Let  $m.w = \max(n.w)$ , if  $m.w = nw_1$ , then the weight  $W$  only updates the first row, and the update weight formula is (3-8) to (3-9):

$$\Delta W_n = n.it * (XR' - W_{n-1}^1) \quad (3-8)$$

$$W_n^1 = W_{n-1}^1 + \Delta W \quad (3-9)$$

Where  $n.it$  is the learning rate and  $W_{n-1}^1$  is the first line of the  $n-1$  weight.

#### 4.2. Experimental verification results and analysis

In this paper, the fitting parameters are obtained by first-order fitting of the extracted effective relative height values, as shown in Table 2. The self-organizing competitive neural network model is established by using the fitting parameters as input. there are 300 sets of data were selected for each working condition as training data, other data as verified data. Its training accuracy rate is 94.67%, and the test accuracy rate is 92.73%. Training results and verification results are shown in Figure 5 and Figure 6;

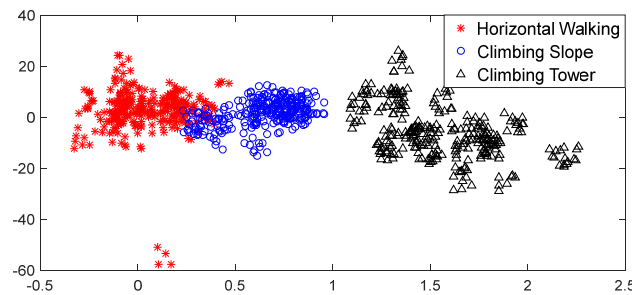


Figure 5. Training condition identification map

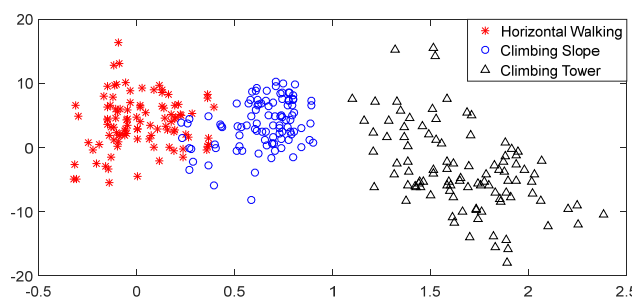


Figure 6. Test condition identification map

## 5. Conclusion

This paper selects an iron tower near the school, a slope with a slope of about  $30^\circ$  and three working conditions of almost horizontal level as the experimental platform. Firstly, each working condition collect 400 sets of data. Then randomly select 300 sets of data from 400 as training data. Finally the rest of the data as verification data. According to the results, the training accuracy rate reached 94.67%, and the test accuracy rate reached 92.73%. It can't only improve the accuracy of related information measurement in power operations, but also has a wide application market.

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