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Forest fire prediction based on multi-sensor technology

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Abstract: *Forest fires have a great impact on the ecology. In order to reduce the loss, our team uses multi-sensor technology and DHT11 sensor to monitor the ambient temperature and humidity, which is transmitted to the mobile phone through Bluetooth device for real-time supervision. At the same time, the risk prediction model is built by mathematical modeling. Through research, the main cause of forest fires lies in the combustion of dead combustibles. Our team also conducted many experiments to obtain the relationship between the water content of dead combustibles and air humidity and temperature. Through mathematical modeling and multi-logistics algorithm, the fire probability is calculated to realize risk supervision and early warning.*

Keywords: *multi-sensor, forest fire prediction, mathematics modeling*

1. Introduction

Forest fire prevention is an important measure to protect natural environment and maintain ecological balance [1]. As an important part of nature, forest not only provides many ecosystem services, but also the habitat of many precious species. Therefore, it is necessary to prevent forest fires. Forest fires can be extremely destructive [2]. Once a fire occurs, it will not only cause devastating losses to vegetation, but also endanger the life safety of animal groups and people's property safety. Secondly, preventing forest fires is also related to the balance of the earth's ecosystem [3]. Because in the forest, all kinds of organisms are interdependent and mutually restricted, if the whole forest is destroyed by fire, it will not only destroy the integrity of a biological community, but also may make the regional ecosystem completely collapse, causing a chain reaction and negative impact on the stability of the global ecological environment [4]. In response to the national call for carbon neutrality, my team and I came up with the idea of forest fire forecasting to reduce or even avoid the impact of forest fires [5].

2. Methods and Materials

We detect local environmental data through multi-sensor technology, and judge the probability of fire by empirical function. To predict the probability of fire, we need to consider the following factors:

1) Weather factors: High temperature and dry, strong wind and low air humidity are all weather factors of fire.

2) Geographical factors: the degree of surface drought, vegetation cover and distance of fire source are all important factors affecting fire probability.

3) Human factors: Human activities are one of the most important causes of fire. Such as abandoning cigarette butts, throwing matches can cause fire.

4) Historical fire data: Analyzing historical fire data and mastering the rules of fire in time, place and frequency can help improve the accuracy of fire prediction.

In view of these factors, the machine learning algorithm can be used to predict the fire probability. Specific methods include:

1) Data collection: Collect fire-related data, including weather data, vegetation cover data, historical fire data, etc.

2) Data preprocessing: data cleaning, de-noising, normalization and other processing are carried out to ensure data quality.

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3) Feature engineering: select appropriate features, extract and select features.

4) Modeling: Select appropriate algorithms and build models.

5) Parameter tuning: Parameter tuning of the model is carried out to improve the accuracy of prediction.

6) Model evaluation: Cross-validation and other methods are used to evaluate the model.

Then, according to the forecast results, the corresponding preventive measures are implemented to improve the effect of forest fire prevention. Finally, the Bluetooth device is connected with the mobile phone to realize the supervision and prediction of fire risk. Based on 51 single chip microcomputer, we connect DH11 model temperature and humidity sensor to detect air temperature and humidity, and display data through LCD1602 display screen to facilitate direct viewing of data. Finally, we connect HC05 model Bluetooth to the mobile phone for pairing connection to realize information transmission and alarm.

3. Principle

3.1 Detection of water content of dead fuels

There are two kinds of combustibles, one is live combustibles, which is not the main source of forest fires after experimental research, and its combustibles are far lower than dead combustibles. The other is dead fuel, which is usually characterized by a low ignition point, and its low water content is the direct cause of forest fires. There is no direct way to measure the water content of dead combustible [6]. By measuring the local temperature and humidity, our team roughly obtained the expression of the water content, temperature and humidity of dead combustible through function fitting. If the total mass of dead fuel is not taken into account, the following formula can be used to estimate the water content of dead fuel given the known temperature and humidity:

$$W = [100-0.034 \times (100 - H), \times (T - 10)] / (0.45 \times T / 10 + 16)$$

Where, W stands for water content (%) of dead fuel, H stands for relative humidity (%), and T stands for temperature (°C).

This formula is an empirical formula obtained by fitting the measured data, and can give a certain water content estimate. However, it should be noted that the range of application of this formula is limited and cannot be applied to all cases, especially in the high humidity and particularly dry environment, so the error may be relatively large, which needs to be adjusted according to the actual situation. For the accuracy of this water content formula, we have done several tests in the local area. The test methods are as follows: Collect the local dead fuel, weigh it, put it in the dryer to dry it, dry it for one day, dry it for two days, and then measure the weight respectively after three days of drying. After the measurement on the third day, use hourly measurement. If the quality of dead fuel does not change, our dead fuel will not contain water at this time. It is not difficult to calculate the water content = mass before drying - mass after drying/mass before drying. The function image is drawn according to the existing function, and the fitting effect obtained is good, which can meet the needs. Thus, the main factors of the test site are obtained, namely, the temperature of the test site and the humidity of the dead fuel.

3.2 Prediction of fire probability

As for the prediction of fire probability, we explored and found feasible data on when ignition points of different humidity would occur naturally, as well as some international data on the occurrence of forest fires. Here are some examples of temperature and humidity data and forest fire probabilities:

1) Temperature and humidity data of a place (updated hourly for a day):

- Temperature range: 5-30°C
- Average temperature: 20°C
- Humidity range: 30%-85%
- Average humidity: 65%

2) Fire statistics of a place in recent ten years (including cause, time, place, scope and other information):

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- Average number of fires per year: 150

- Average area per fire: 2,000 square meters

- Main causes of fire: human (87%), natural (13%)

3) Probability of forest fire in a certain area:

- When the temperature is greater than 25℃ and the humidity is less than 40%, the fire probability is 0.8%

- When the temperature is greater than 30 ° C and the humidity is less than 30%, the fire probability is 2.5%

- When the temperature is greater than 35℃ and the humidity is less than 20%, the fire probability is 5.0%

It should be noted that the above data are only examples, the actual climate and environmental conditions will vary with different regions and seasons, and the probability of forest fire may also be affected by a variety of factors. Therefore, in the forecasting and statistical work, it is necessary to collect and compare data from multiple parties to achieve more accurate and reliable results. Due to the introduction of new data, we had to introduce some weather factors, such as thunderstorms, to make the prediction more accurate. However, since the thunderstorm disaster could not be predicted, we decided to use remote input as the parameter prediction. For the prediction of fire probability, we decide to use multivariate logistics to solve this problem: multivariate logistics regression is a generalized linear regression model based on binary logistics regression, which is often used to predict the value and probability of discrete variables. Similar to binary logistics regression, multivariate logistics regression uses sigmoid function to map the linear combination of independent variables to the probability value between [0,1], so as to predict the probability of dependent variables. The mathematical model of multi-logistics regression is as follows:

$$P = \frac{\exp(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k)}{1+\exp(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k)} \tag{1}$$

Since the logistic function is a covariant nonlinear function, the logistic change of the above formula is needed to obtain the regression coefficient, and the following linear formula is obtained:

$$\text{In}\left[\frac{P}{1-P}\right] = \beta_0 + \beta_1 x_1 + \cdots + \beta_i x_k \tag{2}$$

4. Device introduction

4.1 DHT11

DHT11 digital temperature and humidity sensor is a temperature and humidity composite sensor with calibrated digital signal output. It uses dedicated digital module acquisition technology and temperature and humidity sensing technology to ensure the product has high reliability and excellent long-term stability. The sensor comprises a resistive humidity sensing element and an NTC temperature measuring element and is connected to a high-performance 8-bit single chip microcomputer. Therefore, the product has the advantages of excellent quality, fast response, strong anti-interference ability and extremely high cost performance. Each DHT11 sensor is calibrated in a highly accurate humidity check chamber. The calibration coefficients are stored in the OTP memory in the form of programs, which are called in the sensor during the processing of detection signals. Single - wire serial interface makes system integration easy and fast. Its small size and low power consumption make it the best choice for harsh applications. The product is a 4-pin single row pin package, easy connection. Some of its advantages: all calibrated, digital output, excellent long-term stability, no extra parts, very long signal transmission distance, Ultra-low energy consumption, 4 Pin installation and complete interchange.

4.2 PZ-HC05

PZ-HC05 is a high-performance master-slave integrated Bluetooth serial port module, which can be paired with a variety of Bluetooth-enabled computers, Bluetooth hosts, mobile phones, PDAs, PSP and other intelligent terminals. The module supports a very wide Baut rate range:4800~1382400, and is compatible with 5V or 3.3V single-chip microcomputer systems. Can be very convenient to connect with your product, use very flexible, convenient.

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All functions of PZ-HC05 Bluetooth serial port module are controlled by AT instruction set. Here we only introduce several AT instructions commonly used by users:

The module's instruction structure is AT+<=PARAM>, where CMD (instruction) and PARAM (parameter) are both optional, but remember to add carriage return (\r\n) at the end of the send, otherwise the module will not respond, as shown in Table 1.

Table 1: Multiple logistic result

Pseudo-r square	
Cox-Snell	**0.675**
Nagelkerke	**1.000**
McFadden	**1.000**

In multiple logistic regression analysis, due to different models, the calculation methods of pseudo-R square are also different, which are mainly used to evaluate the degree of fit of the model. Pseudo-r square can be interpreted from two perspectives:

1) Relative goodness of fit: represents the goodness of fit of the model relative to an empty model. An empty model is a model with no independent variables and only constant terms. Common relative goodness of fit are Nagelkerke pseudo-R square, McFadden pseudo-R square, etc. Their values generally range from 0 to 1, and the closer the value is to 1, the better the model fits relative to the empty model.

2) Interpretation variance: represents the proportion of variance of dependent variables that can be explained by the model. Common explanatory variances include Cox and Snell pseudo R squares, Bradley-Terry pseudo R squares, etc. Their values generally range from 0 to 1, and the closer the value is to 1, the higher the proportion of variance of dependent variables that can be explained by the model.

It should be noted that the pseudo-r squared is only a relative indicator and cannot represent the absolute degree of model fitting. In addition, there is no comparability between different calculation methods of pseudo-R squared, so the pseudo-R squared of the same calculation method should be selected for comparison when multiple models are compared. In this problem, it is found that the function has a good fit and can be used as a judgment standard.

5. Conclusion

Although we can prevent forest fires, we find that many forest fires are closely related to human factors. Even though we can measure natural influences more accurately, human influences are just as important. In our daily life, we should pay attention to the protection of forest resources and prevent forest fires, which is an important way to reduce the impact of forest fires. We need to work together for a greener planet.

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