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A Ground Classification Model for Biped Robots Based on Random Fuzzy SVM

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Abstract

In recent years, with the rapid development of humanoid robots, more and more researchers have begun to explore how to endow robots with the ability to perceive the environment. The ground classification can be realized through the tactile information between the robot and the ground. However, the existing research mostly obtains the tactile information through indirect methods. This paper designs a ground classification system of biped humanoid robot based on direct tactile information only. The system cut the signal reasonably by using the sliding window algorithm, and extracts the features of the signal flexibly and effectively by controlling the size of the window. Based on the probability model and decision tree model, we propose a random fuzzy algorithm, which maps the two classifiers into fuzzy multiple classifiers through priori probability, and selects the appropriate filtering algorithm to improve the classification accuracy. In the same data set, the classification accuracy of the random fuzzy algorithm is 92%, and the classification accuracy of the directed acyclic graph algorithm is 89.2%. The random fuzzy algorithm proposed in this paper can assist the biped robot to realize ground recognition only based on direct tactile information.

Keywords

Probability distribution; random variable; SVM; ground classification; biped robot.

1. Introduction

The ground type recognition technology is one of the key technologies of robot environment perception. Efficient and accurate recognition of the current ground type can assist the robot to pass through various complex ground safely. The traditional ground classification algorithm is mainly aimed at wheeled robots. However, at present, the foot robot has a broader development prospect and application value [1,3]. Therefore, it is necessary to study the ground type recognition algorithm suitable for the motion mode of the foot robot.

Mobile robot can be divided into wheeled robot and foot robot according to its movement mode. Since Iagnemma and Dubowsky [4] proposed the ground classification method based on vibration data in 2002, the ground classification of wheeled robots has been a research hotspot, and the relevant methods and theories tend to be perfect and mature [5,7]. However, the foot robot is superior to the wheeled robot in terms of crossing obstacles and appearance, and Hoepflinger [8] proposed a new method of terrain surface classification of leg robot based on tactile information, which verified the feasibility of studying the ground classification of foot robot based on tactile information. The ground classification of foot robot has become a new research hotspot.

The classification methods for the ground classification research of foot robots include back-propagation neural network [9], support vector machine (SVM) [9-14] and deep learning neural network [15]. SVM-based classification algorithm is one of the most widely used and most applicable algorithms. However, due to the limitation of binary classifiers to classify data groups one by one, the recognition rate using SVM classification method may be less than 50%, and there is no good solution for the time being [9].

As the most advanced terrain classification methods are based on force/torque sensors, Cutkosky [13,14] et al. designed a micro tactile sensor array for directly measuring the ground reaction force of a small legged robot, and found that the tactile information obtained by the direct method and the indirect method has very high similarity. However, this method still depends on other sensor data, and cannot achieve terrain type classification only based on tactile information. This is because in the terrain type classification system based only on tactile information, the force/torque sensor data is one-dimensional multi-channel, while the pressure sensor data is one-dimensional single-channel, which greatly increases the difficulty of feature extraction.

In this paper, the sliding window algorithm is used to extract the characteristics of one-dimensional single-channel tactile signals, and the feature selection is realized by selecting the appropriate window size and moving interval. Based on probability theory and decision tree algorithm, a random fuzzy support vector machine (RFSVM) is proposed. Compared with probability classification algorithm and decision directed acyclic graph support vector machine (DDAG SVM), RFSVM has 89.6% accuracy and improves the preference characteristics of the system. RFSVM and DDAG are complementary, and the combination of RFSVM and DDAG can achieve 92% classification accuracy.

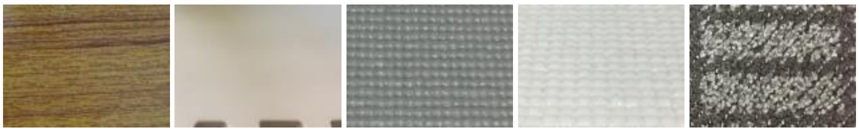
2. Data sets and feature extraction

In this section, we will introduce the data set used in the experiment and the method of extracting the time-domain characteristics of the signal using the sliding window algorithm.

2.1. Data sets

The main working environment of the humanoid robot is indoor. In order to simulate the real working environment of the robot, this paper selects five common indoor ground types. They are hard wood surface, smooth foam surface, smooth carpet surface, rough foam surface and rough carpet surface, which are marked as ground I, ground II, ground III, ground IV and ground V. See Figure 1 for details.

The data set is recorded when the robot walks at a constant walking speed and normal gait. This paper does not discuss the impact of speed on classification results [16,17].



(a) class I (b) class II (c) class III (d) class IV (e) class V

Fig. 1 Physical map of five kinds of ground

This paper controls the speed of KHR-3HV robot by controlling the input frame rate f_{rate}.The frame frequency used is $f_{rate} = 20ms/frame$, the sampling frequency is $f_{sample} = 20Hz$, and the walking speed is $V = 190\ frame/step$, so the data points collected in one step in the experiment is $M = 76$ points. Figure 2 shows the voltage signals collected by the humanoid robot on five kinds of ground.

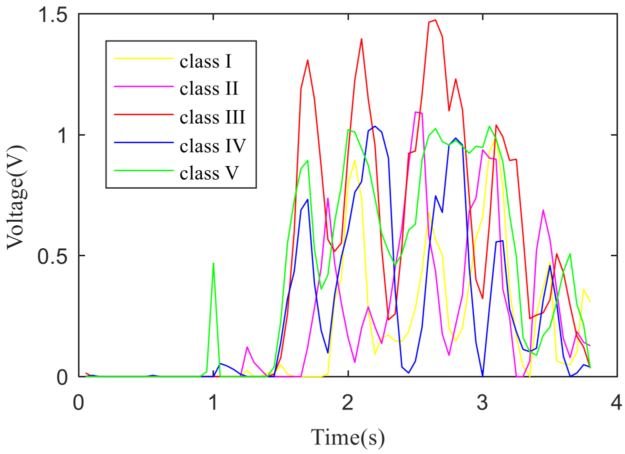


Fig. 2 Voltage signal diagrams collected on five kinds of ground

2.2. Time domain feature extraction by sliding window algorithm

Traditional statistical methods and principal component analysis methods are the mainstream methods of feature extraction in time-domain amplitude analysis, but it is still challenging to effectively extract the feature information of one-dimensional single-channel data collected only based on pressure sensors. In the field of digital signal analysis, the cutting method is commonly used to analyze one-dimensional single-channel signals, that is, a long sequence is cut into several subsequences [18,19], which is successfully converted into a one-dimensional multi-channel signal problem, and then the statistical method and principal component analysis method are used to extract the time-domain amplitude characteristics of the signal. Sliding window algorithm is a special signal analysis method in cutting method.

Figure 3 shows that the sliding window algorithm has four window sliding modes according to the different starting and ending positions of the window. In order to reduce the dimension of feature space, this paper adopts the window sliding mode from B2 to E1. The operation steps of sliding window algorithm are as follows:

Input the original signal x_i whose length is N, $x_i(n)=(x_{i,1},x_{i,2},x_{i,3},\cdots,x_{i,N-1},x_{i,N})$.

Select the appropriate window size W and the interval M for each window movement, and $W \le N$.

The window starts at B2, $Window=[x_l,x_r]$, $x_l=0, x_r=W$.

Intercept the signal in the rectangular frame as the segmented sub-signal S_α, and extract the feature f_α of S_α. $S_\alpha=\{x|x=x_i(n),n\in[x_l,x_r]\}$; $1\le\alpha\le\alpha_{\max}$, $\alpha_{\max}=(N-W)/M+1$.

Move the window to the right by M points. Judge whether constraint F is true. If the condition is true, execute step (4); otherwise, execute step (6).

Output eigenvector $F_i=(f_1,f_2,\cdots,f_{\alpha-1})$.

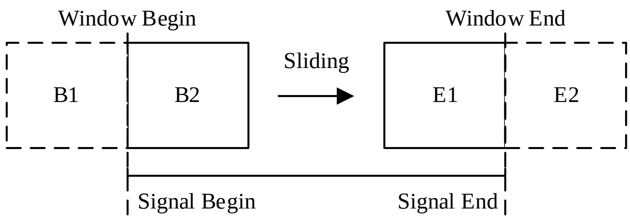


Fig. 3 Schematic diagram of sliding window algorithm

On the premise that the input signal is unchanged, the parameters W and M determine the result of feature extraction. The input signal is F, the window movement interval is F, and the extracted feature vector is marked as F. When F, there is

$$F_i^M = \begin{cases} F_i^1 = \left[f_1, f_2, f_3, \cdots, f_\alpha \right] \\ F_i^2 = \left[f_1, f_3, f_5, \cdots, f_\beta \right] \\ F_i^3 = \left[f_1, f_4, f_7, \cdots, f_\gamma \right] \\ F_i^m = \left[f_1, f_{m+1}, f_{2m+1}, \cdots, f_\lambda \right] \end{cases} \tag{1}$$

And

$$F_i^m \subseteq F_i^1, \quad m = 1, 2, \cdots, N \tag{2}$$

That is, when the window size is fixed, any eigenvector F_i^m is a subset of eigenvector F_i^1. Selecting appropriate parameter M is equivalent to feature selection.

When W is fixed, as M increases, the length of the feature vector decreases rapidly, and the details of the signal can be well preserved. But when M is large enough, a lot of details will be lost. When M is fixed, as W increases, the length of the feature vector decreases, the details of the signal are lost, and the feature curve tends to be smooth.

This paper compares 15 commonly used time-domain amplitude features such as maximum, minimum, average and root mean square, and based on the comprehensive performance of all aspects, the root mean square (RMS) feature is selected finally. Figure 4 shows the root mean square characteristics of five kinds of ground.

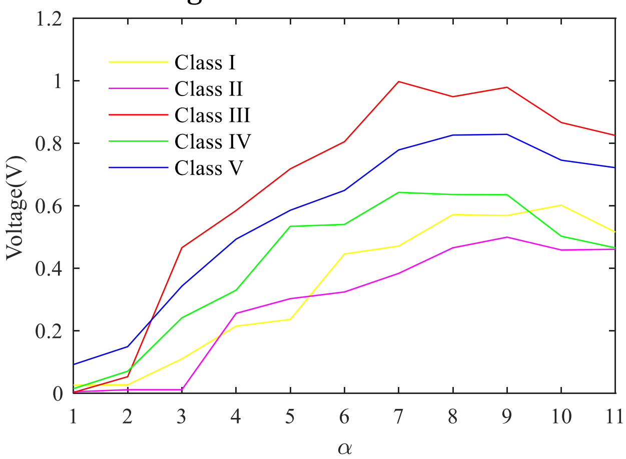


Fig. 4 RMS characteristics of five terrestrial signals

3. Random fuzzy support vector machine

In this section, we will introduce how to use support vector machines and one-to-one algorithms to solve multi-classification problems. Platt [20] et al. proposed directed acyclic support vector machine based on decision tree, but DDAG algorithm has problems of tree node selection and error deposition. In view of these problems, this paper proposes a random fuzzy classification algorithm.

Support vector machine is a machine learning method based on statistical learning theories such as VC dimension theory and structural risk minimization principle [21-24]. As shown in Figure 5, the core idea of SVM-based classification is to construct a hyperplane $g(\boldsymbol{x}) = \boldsymbol{w} \cdot \boldsymbol{x} + b$ in the selected feature space, so that it meets the principle of maximizing the classification interval and separate the training sample points as far as possible. The standard hyperplane is shown in Formula 3.

$$\begin{gathered} \min_{\boldsymbol{w},b} \frac{1}{2} \|\boldsymbol{w}\|_2^2 \\ y_i \left(\boldsymbol{w} \cdot \boldsymbol{x}_i + b \right) \geq 1 \quad , i = 1, 2, \cdots, l \end{gathered} \tag{3}$$

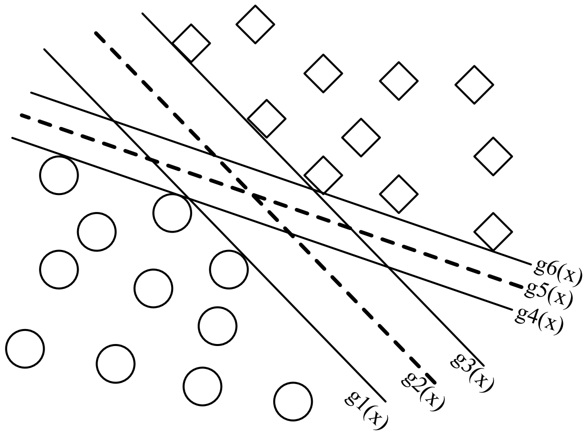


Fig. 5 RMS characteristics of five terrestrial signals

The standard SVM was originally used to solve the binary classification problem, so the multi-classification problem is often transformed into a binary classification problem that is easier to handle. The core idea of the one-to-one algorithm proposed by KreBel [25] is to construct $C(C-1)/2$ binary classifiers to solve an C class problem. In this paper, a random fuzzy support vector machine is proposed based on one-to-one algorithm and probability theory. The accuracy of the algorithm is equivalent to that of DDAG, but the design idea is simple, and it can also be combined with DDAG to achieve higher classification accuracy.

Take three classifications as an example. First, we need to transform three types of problems into three types of two classification problems, and define the two classifiers composed of class i and class j as B_{ij}.

$$B_{ij}(\boldsymbol{x}) = \begin{cases} 1 & ;\text{Positive} \\ 0 & ;\text{Negative} \end{cases} \quad ;ij = 12,13,23 \tag{4}$$

For the known input k, the probability of two classifiers B_{ij} to distinguish it as class i is $P^{+}_{k,ij}$, and the probability of distinguishing it as class j is $P^{-}_{k,ij}$.

$$P^{+}_{k,ij} + P^{-}_{k,ij} = 1, ij = 12,13,23 \tag{5}$$

Definite $\Phi_{ij} = \left[\phi_{1,ij}, \phi_{2,ij}, \phi_{3,ij}\right]^{T}$.

$$\phi_{k,ij} = \begin{cases} \dfrac{P^{+}_{k,ij}}{P^{+}_{1,ij} + P^{+}_{2,ij} + P^{+}_{3,ij}}; B_{ij} = 1 \\ \dfrac{P^{-}_{k,ij}}{P^{-}_{1,ij} + P^{-}_{2,ij} + P^{-}_{3,ij}}; B_{ij} = 0 \end{cases} \quad ;ij = 12,13,23 \tag{6}$$

Φ_{ij} means that for the unknown class input sample x, when the output of the second classifier B_{ij} is 1 or 0, the system thinks that the possibility of $\phi_{1,ij}$ is Class 1, the possibility of $\phi_{2,ij}$ is Class 2, and the possibility of $\phi_{3,ij}$ is Class 3.

For a five-class problem, we need to construct 10 secondary classifiers, which are marked as B_n, $n = 0,1,\cdots,8,9$. For the input sample x, the probability distribution function $\Phi_n(\boldsymbol{x})$ about x can be obtained from the output of the two classifiers B_n. The highest probability category can be obtained by superposing all prior probabilities $\Phi_n(\boldsymbol{x})$ with probability classification method. However, this method makes the system have serious decision preference, so random number is introduced to eliminate that.

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The probability distribution function $\Phi_n(\boldsymbol{x})$ is mapped to the interval [0,1], and the probability distribution density function $\phi_n(\boldsymbol{x})$ is obtained. The points in the real number space [0,1] correspond to each category. The probabilities of any point in the interval belonging to Class I, Class II, Class III, Class IV and Class V are $\phi_{1,n}, \phi_{2,n}, \phi_{3,n}, \phi_{4,n}$ and $\phi_{5,n}$, respectively, as shown in Figure 6. At this time, the interval [0,1] can be regarded as a multiple classifier, and the input x is replaced by the random number r of the interval [0,1]. The same input x may be mapped to different random numbers, so x may be assigned to different classes, so it is called random fuzzy algorithm.

Fig. 6 The probability distribution density function $\phi_n(\boldsymbol{x})$

The accuracy of a single random fuzzy multiple classifiers is very low, and can be improved by combining multiple classifiers. The algorithm first selects the two categories with the highest number of votes, and then makes decisions through a layer of SVM. The algorithm flow is shown in Figure 7. In the figure, "i vs j" represents the SVM secondary classifier trained with class i as positive samples and class j as negative samples. The probability distribution function corresponding to input x is $\boldsymbol{P}(k)=\boldsymbol{P}_{pos}$ (or $\boldsymbol{P}(k)=\boldsymbol{P}_{neg}$) according to the positive (or negative) output of SVM.

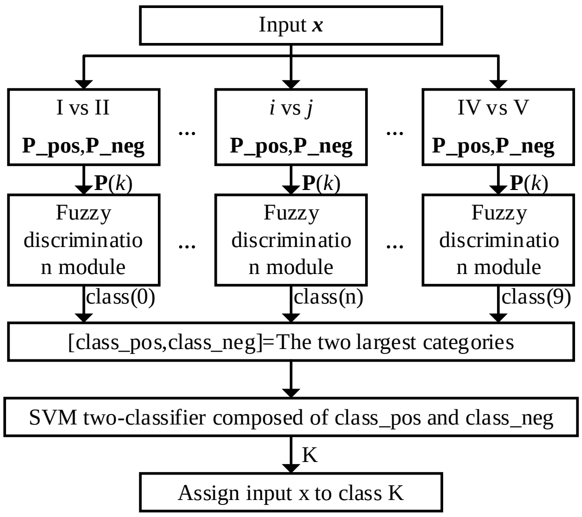

Fig. 7 Flow chart of random fuzzy algorithm

Since the RFSVM algorithm uses random number r to replace input x, it can repeatedly input x and extract the features of the output sequence to improve the accuracy. As shown in Figure 8, the RFSVM algorithm is cycled several times until the output sequence meets the sequence feature screening requirements.

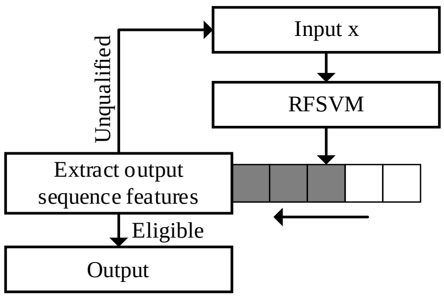

Fig. 8 Loop RFSVM Algorithm

4. Experimental result

Each of the five ground training sets is 120 sets. The moving window algorithm is used to extract RMS features as the training set of the classifier, and the same method is used to generate the test set.

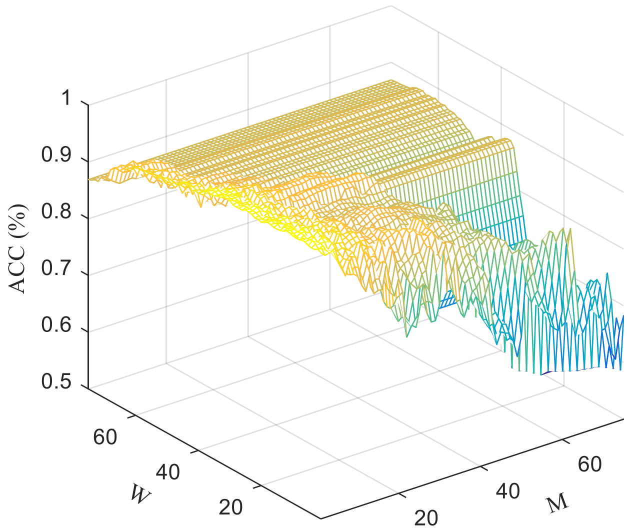

Fig. 9 Accuracy of different W and M

The influence of window size W and moving interval M on the accuracy of the classifier is shown in Figure 9. The relationship between W , M and accuracy is complex and nonlinear, so we should treat them as a whole. They also determine the dimension of feature space, so the final choice in this paper is $W=26; M=5$.

The classification results of five ground test sets using probabilistic classification, RFSVM and DDAG SVM algorithms are shown in Table 1. P represents the ratio of the number of classes I that are correctly classified to the total output of classes I. R represents the ratio of the number of classes I that are correctly classified to the total input of classes I.

The accuracy of RFSVM algorithm is equivalent to that of DDAG algorithm, which is 89.6% and 89.2%. The standard deviation of recall rates for all class using probabilistic classification, RFSVM and DDAG algorithms is 0.095, 0.077 and 0.082. The minimum standard deviation of RFSVM algorithm shows that it can effectively improve the preference characteristics of the system. Class I and Class III using RFSVM have high recall rate, and its accuracy reaches 99.6% and 100%. If the input is recognized as Class I or Class III by RFSVM, the probability of its actual being class I or class III is 99.8%. This is important for robots to respond and add new classes to the database.

RFSVM algorithm has high accuracy and recall rate for class I and class III. Due to the use of random numbers, RFSVM and DDAG algorithms have nonlinear correlation. The accuracy of the system can be further improved by combining RFSVM and DDAG algorithm.

This paper compares three methods for extracting the features of output sequence: 1) The first occurrence of a duplicate class in the output sequence, 2) At least two of the three consecutive output sequences are the same, and the number of cycles is not limited, 3) At least two of the three consecutive output sequences are the same, and the number of cycles is limited to no more than five. The accuracy of the three methods is 90.0%,92.0%,91.8%, see Table 2 for details.

The higher the limit of output feature, the higher the accuracy of the system, and the higher the time cost of corresponding recognition. The accuracy of no more than five cycles is very close to that of unlimited cycles. In practical applications, the accuracy and time cost can be balanced by setting sequence characteristics and limiting the number of cycles.

Table 1 Classification results using Probability, RFSVM and DDAG algorithms

Algorithm	Project	Class Ⅰ	Class Ⅱ	Class Ⅲ	Class Ⅳ	Class Ⅴ
Probability	P(%)	93.7	86.0	96.5	85.3	85.3
	R(%)	99.2	76.7	91.7	82.5	96.7
RFSVM	P(%)	99.6	81.2	100	81.5	86.7
	R(%)	94.4	81.0	98.1	81.9	92.7
DDAG	P(%)	92.2	81.8	98.2	85.6	88.1
	R(%)	99.2	82.5	92.5	79.2	92.5

Table 2 Classification results of three schemes

Algorithm	Project	Class Ⅰ	Class Ⅱ	Class Ⅲ	Class Ⅳ	Class Ⅴ
Method 1	P(%)	92.3	76.9	100	85.3	97.2
	R(%)	100	83.3	98.3	82.5	85.8
Method 2	P(%)	96.8	79.8	100	86.4	98.2
	R(%)	100	85.8	98.3	85.0	90.8
Method 3	P(%)	96.8	80.8	100	86.0	96.4
	R(%)	100	84.2	98.3	86.7	90.0

5. Conclusion

The RFSVM algorithm can realize the ground classification and recognition of mobile robots only based on one-dimensional single-channel tactile information. The core idea of RFSVM is to map two classifiers into multiple classifiers by mapping method based on prior probability, and then improve the accuracy by voting decision and filtering algorithm. The accuracy of RFSVM is 89.6%, which is equivalent to that of DDAG algorithm, but the recall rate of all kinds is balanced, which can better improve the preference characteristics of the system. Class I and Class III have high accuracy and recall rate, which makes RFSVM have better development potential and can be more easily integrated with other algorithms. The accuracy of combined RFSVM and DDAG is 92.0%.

Different output sequence feature extraction methods can further improve the overall classification accuracy of the algorithm. The time cost of higher accuracy algorithms will increase accordingly. In practical applications, it is necessary to choose between them.

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