Application Research of Support Vector Machine in Fall Detection of Old People

Yufeng Yang[1, a, *]

[1]Guangdong University of Science & Technology, Dongguan 523083, China.

[a]E-mail: 294054110@qq.com

Abstract

With the development of urbanization, the elderly have become a common phenomenon. It is followed by the elderly who fall indoors because they cannot be treated in time, causing serious consequences, and even deaths occur from time to time. Therefore, the fall detection of the elderly has attracted the attention of many experts and scholars. However, due to the diversity of human activities in daily life and the complexity of the scene, the reliability and robustness of the fall detection of the elderly has been severely limited. Aiming at the fuzzy characteristics of the characteristic parameters of the fall of the elderly, this paper uses the least squares method to optimize the parameters of the support vector machine, and establishes the old-fashioned fall identification model of the least squares support vector machine. The research results show that the relative error of the old people's fall recognition model based on the support vector machine has higher detection accuracy.

Keywords

Old man falls; least squares method; support vector machine.

1. Introduction

There is no obvious boundary between the old man's fall or normal human movement, which is consistent with the dynamic model of nonlinear structure. Due to the uncertain factors such as complex and variability of model parameters, it is difficult to accurately express it using classical mathematical modeling methods. Support Vector Machine (SVM) is a machine learning method based on statistical learning, multidimensional theory and structural risk minimization. To a large extent, it has overcome problems such as “dimensional disaster” and “over-learning”. Support vector machine has a perfect theoretical foundation and can simplify the mathematical model of complex problems. Therefore, it is widely used in fields such as face recognition, remote sensing classification and pattern recognition without strict demarcation. In recent years, many scholars have supported the vector machine into the discrimination of the elderly, and achieved good results. On the basis of summarizing the research of predecessor support vector machine, this paper studies and discusses the support vector machine in the fall of the elderly, and prospects the development of support vector machine.

2. Support Vector Machine

SVM is a classifier developed from the generalized portrait algorithm in pattern recognition [1]. Its early work was from a study published in 1963 by former Soviet scholars Vladimir N. Vapnik and Alexander Y. Lerner. In 1964, Vapnik and Alexey Y. Chervonenkis further discussed the generalized portrait algorithm and established a linear SVM with hard margins. Later in the 1970s and 1980s, with the theoretical study of the maximum margin decision boundary in pattern recognition[2], the emergence of programming problem solving techniques based on slack variable, and VC dimension (Vapnik) -Chervonenkis dimension, VC dimension), SVM is gradually theorized and becomes part of the statistical learning theory [1]. In 1992, Bernhard E. Boser, Isabelle M. Guyon and Vapnik obtained the first nonlinear SVM through the nuclear method[3]. In 1995, Corinna Cortes and Vapnik proposed a nonlinear SVM with soft margins and applied it to handwritten digit recognition. This research has received extensive attention and citation since its publication, and its subsequent SVM in various fields. The application laid the foundation.

The SVM uses the hinge loss function to calculate the empirical risk and adds a regularization term to the solution system to optimize the structural risk. It is a classifier with sparsity and robustness. SVM can be nonlinearly classified by the kernel method, which is one of the common kernel learning methods.

3. Nonlinear Support Vector Machine and Kernel

For nonlinear problems, linear separable support vector machines are not effectively solved, and nonlinear models are used to classify them well. First look at an example, as shown in Figure 1, the green for the detected normal movement of the elderly in the sample, the red for the detected is the data sample of old man fell down, in the middle of the judgment in the error or no judgment in the data sample.

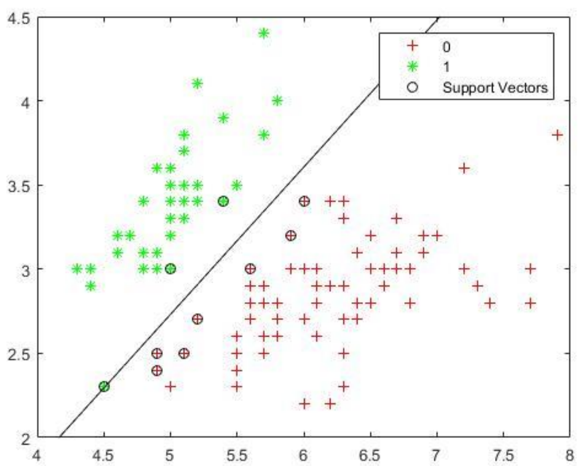

Figure 1. Linear Support Vector Machine

It is clear that using a linear model does not separate the two types of samples, but they can be separated using a nonlinear model. However, the nonlinear problem is often difficult to solve, so it is hoped that it can be solved by solving the linear classification problem. Therefore, nonlinear transformation can be used to transform the nonlinear problem into a linear problem. For such problems, the training samples can be mapped from the original space to a higher-dimensional space, so that the samples are linearly separable in this space. If the original spatial dimension is finite, that is, the attributes are finite, then there must be one The high dimensional feature space makes the sample separable. Letφ(x) denote the eigenvector with x mapped, then in the feature space, the model corresponding to the hyperplane can be expressed as:

$$f(x) = wT\Phi(x) + b \tag{1}$$

So there is a minimized function:

$$\min_{w,b} \frac{1}{2}\|w\|^2 \tag{2}$$

$$s.t. y_i(w^T\Phi(x_i) + b) \geq 1(i = 1, 2...., m) \tag{3}$$

The dual problem of the equation is:

$$\max_{a}\sum_{i=1}^{m}a_i-\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}a_ia_jy_iy_j\phi(x_i)^T\phi(x_j) \tag{4}$$

$$s.t.\sum_{i=1}^{m}a_iy_i=0,\quad a_i\geq 0,\ \ i=1,2,...,m \tag{5}$$

Solving the equation needs $\phi(x_i)^T\phi(x_j)$ to be calculated. $\phi(x_i)^T\phi(x_j)$ is the product of the sample x_i and x_j the feature space mapping. Since the dimension of the feature space may be very high or even infinite, the direct calculation $\phi(x_i)^T\phi(x_j)$ is usually difficult, so I think of such a function:

$$k(x_i,x_j)=<\phi(x_i),\phi(x_j)>=\phi(x_i)^T\phi(x_j)$$

That is, the inner product of xi and xj in the feature space is equal to the function value they calculated in the original sample space by the function $k(x_i,x_j)$, and then the formula 4 is written as follows:

$$\max_{a}\sum_{i=1}^{m}a_i-\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}a_ia_jy_iy_jk(x_i,x_j) \tag{6}$$

In summary, the solution is available:

$$s.t.\sum_{i=1}^{m}a_iy_i=0,\quad a_i\geq 0,\ \ i=1,2,...,m \tag{7}$$

$$\begin{aligned}f(x)&=w^T\phi(x)+b\\&=\sum_{i=1}^{m}a_iy_i\phi(x_i)^T\phi(x_j)+b\\&=\sum_{i=1}^{m}a_iy_ik(x)+b\end{aligned} \tag{8}$$

The simulation test was performed using Matlab. The results are shown in Figure 2. The green sample represents the normal exercise data of the elderly, the red sample represents the old man falling to the data, and the middle -1 to 1 can adjust the threshold according to the specific situation. The red data sample and the green data sample are separated by two ellipses. It has high recognition accuracy.

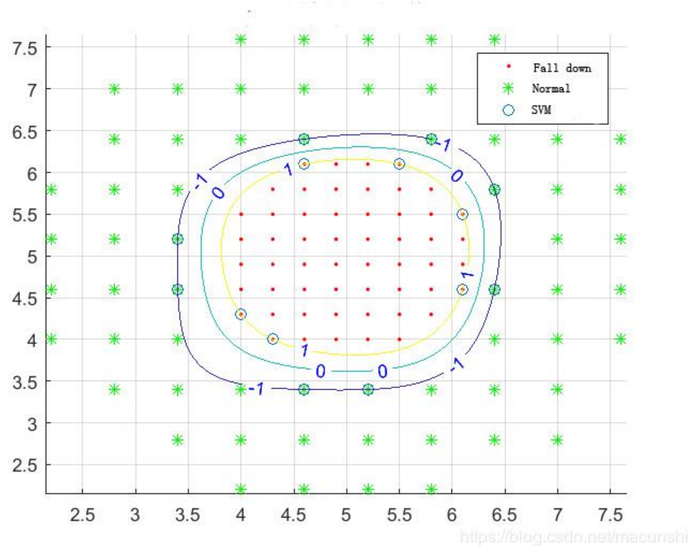

Figure 2. Nonlinear Support Vector Machine

In this example, the function $k(x_i, x_j)$ is a polynomial kernel function. In practical application, different kernel functions can be selected according to the specific situation and the characteristics of different sample data, and the parameters of the kernel function can be modified according to the specific situation, so as to achieve the best effect of the system operation. The commonly used kernels are shown in Table 1.

Table 1. The commonly used kernels

Name	Expression	Parameter	
Linear kernel	$k(x_i, x_j) = x_i^T x_j$		
Polynomial kernel	$k(x_i, x_j) = (x_i^T x_j)^d$	$d \ge 1$ s the number of polynomials.	
Gaussian kernel	$k(x_i, x_j) = \exp(-\frac{\lVert x_i - x_j \rVert^2}{2\delta^2})$	$\sigma > 0$ is the bandwidth of Gauss	
Laplacian kernel	$k(x_i, x_j) = \exp(-\frac{\lVert x_i - x_j \rVert}{\delta})$	$\sigma > 0$	
Sigmoid kernel	$k(x_i, x_j) = \tanh(\beta x_i^T x_j + \theta)$	Tanha is hyperbolic tangent function. $\beta > 0, \theta < 0$	

4. Conclusion

This paper systematically introduces the application of support vector machine in falls detection of the elderly. This paper focuses on the theoretical deduction process of the non-linear support vector machine and its application in the detection of falls in the elderly. Based on the polynomial kernel function, the MATLAB simulation experiments on the data samples were carried out to verify the high accuracy of the non-linear support vector machine in the fall detection of the elderly. Finally, the commonly used kernels are introduced.

References

[1] Hsieh, W.W. Machine learning methods in the environmental sciences: Neural networks and kernels: Cambridge university press, 2009: Chapter 7, pp.157-169.

[2] Qin, J. and He, Z.S., 2005, August. A SVM face recognition method based on Gabor-featured key points. In Machine Learning and Cybernetics, 2005. Proceedings of 2005 International Conference on (Vol. 8, pp. 5144-5149). IEEE.

[3] Vapnik, V.N. and Lerner, A.Y., 1963. Recognition of patterns with help of generalized portraits. Avtomat. i Telemekh, 24(6), pp.774-780.