Research on Skin Roughness Classification Based on Improved SVM

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Abstract. Skin condition closely reflects human health, and skin roughness is one of the factors to analyze skin condition. This paper presents a classification algorithm of skin roughness based on improved support vector machine. The improved gray co-occurrence matrix, Tamura texture feature, fractal dimension, Gabor feature and other 24 properties affecting skin roughness were extracted by using human skin samples captured by visible light as data sources. Genetic algorithm was used to optimize the feature space, and the most important feature combinations were selected according to the fitness values. In order to improve the performance of classifier, the improved particle swarm optimization algorithm is used to optimize the penalty factor C and radial kernel function coefficient Gamma of support vector machine. The experiment shows that the model established in this paper has an obvious effect on the classification of skin roughness.

1. Introduction

The skin attached to the body surface not only protects the human body, its state is also closely related to human health. The roughness of the skin as a basis for measuring skin condition indicators, the analysis of skin wrinkles, elasticity, pigmentation, aging as well as pathological conditions play an important role. Therefore, the research on skin roughness classification has certain practical significance.

The traditional roughness evaluation is mainly based on manual evaluation, which is subjective and cannot be objectively and quantitatively analyzed. With the development of camera imaging and storage technology in recent years, machine vision has created new ideas and methods for evaluating skin roughness. Support vector machines are generally used to solve two classification problems. It is a classic two classification model. Its basic model defines a linear classifier with the largest interval in the feature space. The largest interval makes it different from the perceptron. Compared with neural networks, SVM has outstanding advantages in solving linear inseparable problems. Zhichao Shen[1] and others proposed color pre-segmentation processing and GA-SVM classification method for the damaged peanut skin to solve the problems of inaccurate classification and poor generalization ability. Bin Dong[2] proposed a PSO parameter optimization algorithm with particle position weight and correlation function between particles for pathological image classification, which improved the accuracy of SVM classification. Jianwei Zhou[3] proposed a method based on median robust extended local binary pattern (MRELBP), Franklin moments and cuckoo optimized SVM to improve the
recognition accuracy of remote sensing image building areas. Baosheng Li[4] performs PCA dimensionality reduction on multiple attributes that affect the price of electric vehicles to obtain more important sample attributes. Then the data was classified by SVM optimized by particle swarm, and a good classification effect was achieved. Therefore, the classification accuracy can be effectively improved by optimizing SVM. The experimental analysis of pre-way optimization of Particle Swarm Optimization for SVM classification roughness of the skin has a good effect.

2. The Related Method

2.1. SVM

SVM is a traditional two-class model, the basic principle is to establish an optimal classification hyperplane, so that the ultra-right plane at the same time separate the different samples, but also to maximize the spacing so that the sample classification. When the sample is nonlinear state, the raw data space \( \Phi(x) \) needs to be projected onto the new mapping function, defining a new decision boundary. Therefore, the initial form of the loss function of the nonlinear SVM is:

\[
\begin{align*}
\min_{w,b} & \quad \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{N} \xi_i \\
\text{subject to} & \quad y_i (w \cdot \Phi(x_i) + b) \geq 1, \\
& \quad \xi_i \geq 1, i = 1, 2, \ldots N
\end{align*}
\]

(1)

Where \( w \) is the normal vector of the hyperplane, \( \xi_i \) is the slack variable, \( C \) is the penalty factor, \( x_i \) is the \( i \)-th sample feature, and \( y_i \) is the category label. From this, we can get the optimization problem of SVM Lagrangian function and Lagrangian dual function:

\[
L(w,b,a) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^{N} \alpha_i (y_i (w \cdot \Phi(x_i) + b) - 1)
\]

(3)

\[
L_\alpha = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i \alpha_j y_i y_j \Phi(x_i) \Phi(x_j)
\]

\[
\text{subject to} \quad \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_i y_i = 0, 0 \leq \alpha_i \leq C, 1, 2, \ldots N
\]

(4)

From (3)(4), the optimal decision boundary function can be obtained:

\[
f(x) = \text{sign}(w \cdot \Phi(x) + b)
\]

\[
= \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i \Phi(x_i) \cdot \Phi(x) + b\right)
\]

(5)

Among them, \( \alpha_i \) is the Lagrangian multiplier and \( \Phi(x_{test}) \) is any test sample. In order to solve the problem that the dot product dimension of feature space \( \Phi(x_i) \cdot \Phi(x_{test}) \) is too high, the Kernel Function is quoted:

\[
K(x_i, x_{test}) = \Phi(x_i) \cdot \Phi(x_{test})
\]

(6)

SVM mainly addresses the problems of two types of samples, and most problems exist in the form of multiple classifications. Common combination classifiers include one-to-one multi-classifiers, one-to-other multi-classifiers, and directed acyclic graph multi-classifiers. In view of the fact that the classification of skins is only 3 categories, the one-to-one (OVO) classifier method is initially selected. The OVO method refers to a multi-classification problem with a category number of \( k \), and constructs a two-classifier for each two categories. Construct a \( k(k-1)/2 \) classifiers, each of which is as follows:
The formula (7) shows a two-class classifier trained with category \( s \) and category \( t \) as examples, and its decision function

\[
f_{st}(x) = \text{sign}(w_{st} \cdot \Phi(x) + b_{st})
\]

For each pair of classifications, the output category of the two classifiers is obtained under the action of the decision function, and all \( k(k-1)/2 \) classification results are voted by the voting method, and the category with the highest votes is the output result of the multi-classifier.

2.2. Basic particle swarm algorithm

The particle swarm algorithm is an algorithm based on swarm intelligence optimization\[^5\]. It is assumed that the problem space is \( d \)-dimensional and the population size is \( M \). Each particle in the population represents a feasible solution, with two vectors of position and velocity, and a fitness value determined by the objective function. Let \( X_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \) and \( V_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \) be the position and velocity of the \( i \)-th particle, and \( p_b = (p_{b1}, p_{b2}, \ldots, p_{bd}) \) and \( g_b = (g_{b1}, g_{b2}, \ldots, g_{bd}) \) are the optimal position of the \( i \)-th particle and the optimal position of the entire particle swarm. In the whole iteration process, the particle can update its own speed and position through the individual extreme value \( p_b \) and the group extreme value \( g_b \), as shown in formula (9)(10):

\[
v_{ij}^{k+1} = e v_{ij}^k + c_1 v_{ij} (p_{b,j} - x_{ij}^k) + c_2 v_{ij} (g_{b,j} - x_{ij}^k)
\]

\[
x_{ij}^{k+1} = x_{ij}^k + v_{ij}^{k+1}
\]

Where \( e \) is the weight of inertia, \( c_1 \) and \( c_2 \) are learning factors, \( r1 \) and \( r2 \) are random numbers in the interval \( [0,1] \), \( k \) is the algebra of evolution, and \( 1 \leq i \leq M \), \( 1 \leq j \leq d \).

3. Algorithm Flow

3.1. Overall Process

Skin roughness measures the smoothness of the skin. Smooth skin is generally smooth, bright and elastic. With the change of age and other factors, the skin will become less firm, grainy and wrinkles will increase, and stains will gradually become apparent. Therefore, the roughness of the skin reflects the aging degree of the skin and represents the age and health of the skin. As shown in the skin roughness level in Figure 1, the skin images in Figure 1(a) are smoother and tighter, without obvious wrinkles and furrows; the skin shown in Figure 1(b) has significantly more wrinkles than 1(a). Reduced firmness. Figure 1(b) Increased skin oil content, deep wrinkles, and larger skin particles with sparse texture.
For skin characteristics, from a visual perspective, the size of the texture primitive is used as the reference condition for judging the roughness. The larger the primitive size, the lower the texture density, the rougher it will be.

The overall process is shown in Figure (2). The skin image is extracted from multiple dimensions of texture features, and then genetic algorithms are used to screen and optimize the extracted texture features, and the highly correlated ones are extracted as classification features. According to the extracted features, the penalty factor and radial kernel function coefficient of SVM are optimized by particle swarm optimization. After optimization, the optimal parameters are obtained to participate in the classification calculation of SVM, and finally the classification results are evaluated.
3.2. Feature Extraction

3.2.1. LBP-GLCM
Since the texture is based on the periodic distribution of image gray levels, corresponding pixels at a certain distance in the gray level image have gray-level connections, that is, spatial correlation, so the gray-level co-occurrence matrix is used to calculate texture features. However, the quantization of gray levels will lose a lot of original details, which reduces the reliability of the feature information obtained from the gray level co-occurrence matrix. LBP has rotation invariance, effectively reflects the correlation information between pixels and neighboring pixels, and the calculation is small and fast. The gray-level co-occurrence matrix combined with local binary mode can effectively solve this problem. Calculate the Entropy, Inverse Moment, Contrast and Correlation index of the gray level co-occurrence matrix $O(\theta)$ in LBP mode, and then calculate the four indexes in each direction and the average value and variance. Among them, the Entropy, Inverse Moment, Contrast and Correlation are as formula (11-14) shows:

\[
\text{ENT} = -\sum_{i,j} p(i,j) \log_2[p(i,j)]
\]

\[
\text{IDM} = \sum_{i,j} p(i,j) / [1 + (i-j)^2]
\]

\[
\text{CON} = \sum_{i,j} (i-j)^2 p(i,j)
\]

\[
\text{COR} = \left[ \sum_{i,j} (i+1)(j+1)p(i,j) - \mu x \mu y \right] / \sigma x \sigma y
\]

3.2.2. Tamura Feature
Tamura texture feature is based on human visual perception of texture, which mainly includes six components, namely Coarseness, Contrast, Directionality, Line Likeness, Regularity And Roughness, for skin texture images, the first four components are mainly analyzed and calculated. The calculation process of Roughness is to calculate the average intensity value of pixels in the active window of $2^k \times 2^k$ pixels in the image.

\[
A_k(x, y) = \sum_{i=2^{k-1}}^{2^k-1} \sum_{j=2^{k-1}}^{2^k-1} g(i,j) / 2^{2k}
\]

Where $k=1,2,...5$, $g(i,j)$ is the intensity value of the pixel located at $(i, j)$. Then calculate the average intensity difference between the windows that do not overlap each other in the horizontal, vertical, and diagonal directions for each pixel to reach the maximum $k$ value to set the optimal size $s(k, i, j) = 2^k$.

Then the formula of Tamura Roughness can be derived as:

\[
F_c = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} s_b(i, j)
\]

3.2.3. Fractal Dimension
Fractal dimension is the quantitative characterization and basic parameter of fractal theory. It is usually expressed by fractions or decimals. It describes a quantity of the complexity of fractal collection and quantitatively expresses the complexity or irregularity of the image. The skin images have similar textures, so the roughness can be fractalized as a ratio, providing a statistical index. The box technique is used to calculate the fractal dimension of the skin image, and the fractal dimension $\text{dim}(S)$ of the image and the error size $E$ are used as the feature index. Assuming a set $S$, the expression of fractal dimension is:

\[
\text{dis}(S) = \lim_{\varepsilon \to 0} \frac{\log(N(\varepsilon))}{\log(1/\varepsilon)}
\]
3.2.4. Gabor Feature

Gabor is a frequency transformation method. Because its function is similar to the biological function of the human eye, it can model the sensitive characteristics of the frequency and direction of the human visual system for texture analysis [8]. The essence of Gabor transform is to convolve a two-dimensional image. Through the selection of frequency parameters and Gaussian function, Gabor transform can select many texture features. The expression of the two-dimensional Gabor function is:

\[
g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + y'^2}{2\sigma^2}\right) \exp\left(i(2\pi \frac{x'}{\lambda} + \psi)\right)
\]

where \(x' = x \cos \theta + y \sin \theta\), \(y' = -x \sin \theta + y \cos \theta\).

\[\lambda\] is the wavelength of the sine function, \(\theta\) is the direction of the kernel function, \(\psi\) is the phase shift, \(\sigma\) is the Gaussian standard deviation, and \(\gamma\) is the aspect ratio in the x and y directions. In order to extract the Gabor feature, the processed image is divided into blocks, and n equal divisions are taken in the horizontal and vertical directions respectively, and 5 different directions (0, \(\pi/5\), 2\(\pi/5\), 3\(\pi/5\), 4\(\pi/5\)) Remove the feature vector, the corresponding energy of each block is:

3.3. GA-based feature selection optimization

A large number of features will reduce the classification performance of the SVM. In order to improve the classification effect, the genetic algorithm is used to screen and optimize the obtained features, so that the correlation of the classified feature data is enhanced. Genetic algorithm is a kind of algorithm that imitates biology. It searches and determines the optimal solution of the problem by simulating the evolution of biology [9]. The main process is as follows:

Step1: Perform individual coding on the optimized feature, set the dimension to D, and the coding of a single feature is expressed in binary.

Step2: Establish an initial population, and treat all possible solutions to the original problem of the algorithm as individuals of the population. The size of the population represents the size of the algorithm's random search space. Set the initial population size to 30.

Step3: Select fitness function. The fitness function represents an individual's ability to adapt to the environment and is an index used to judge the pros and cons of individual performance in the population. The separability criterion based on the distance within the class is adopted, and the FISHER linear discrimination is used as the fitness function of the population. Let denote the mean vector of the i-th sample set, A denotes the total mean vector of various sample sets, B is the prior probability, C is the number of samples, D is the number of categories, and G is the D-dimensional feature vector in the class, then express The formula is:

\[
J(x) = \frac{\text{tr}\tilde{S}_x}{\text{tr}\tilde{S}_w}
\]

\[
\tilde{S}_x = \sum_{i=1}^{c} \frac{1}{n_i} \sum_{k=1}^{n_i} (x_k^i - m_i)(x_k^i - m_i)^T, \quad \tilde{S}_w = \sum_{i=1}^{c} \frac{1}{n_i} \sum_{k=1}^{n_i} (x_k^i - m_i)(x_k^i - m_i)
\]

Step4: Crossover and mutation. The crossover operator replaces part of the genes of the two parent individuals to recombine to generate two new individuals. A random set intersection individual population coding feature, the cross operation, part of the coding interchanged two points before and after the intersection. The mutation operator changes the gene at a certain position encoded by the individual of the characteristic population, while keeping the number of features in the chromosome after mutation unchanged.

Step5: Repeat iteration. set the algebra of population evolution to 100 generations, and then perform selection, crossover and mutation operations, the chromosomes in the population will tend to the optimal solution in the number of features, after 100 iterations, output the final population fitness. The largest chromosome is to select d optimal features in D dimension.
3.4. Adaptive particle swarm optimization SVM

Before using the SVM prediction model for classification, it is necessary to determine the kernel function type, penalty coefficient C, and kernel function parameter g. The size of C affects the training error, if C is too small, the training error will be larger and thus affect its generalization ability; g controls the sensitivity of the SVM to the input variables. Only by selecting appropriate parameters can accurate prediction be achieved. In order to select parameters reasonably, the adaptive particle swarm optimization SVM method is used to optimize the above two parameters.

The particle swarm algorithm has fast convergence speed and simple algorithm. It is widely used in image processing and other fields. However, the algorithm is easy to fall into the local optimum, cannot obtain the global optimum solution, and relies too much on inertia weight. The size of \( e \) affects the weight of global search ability and local search ability. Therefore, the adaptive particle swarm algorithm is used to dynamically change the weight \( e \) of each particle in the population according to the size of its fitness value, so that the global and local optimal abilities of the particles reach a dynamic balance. The function of the adaptive weight is as (20) shows:

\[
e_{i} = \max_{e} - \frac{\max_{e} - \min_{e}}{1 + \exp \left( \frac{f_{i} - f_{\text{avg}}}{f_{g} - f_{\text{avg}}} \right)}
\]

(20)

Among them, \( e_{\max} \) and \( e_{\min} \) represent the maximum and minimum weights respectively, \( f_{i} \) is the fitness value of the \( i \)-th particle, \( f_{g} \) is the optimal fitness value of the entire population, and \( f_{\text{avg}} \) is the average fitness value of the entire population.

The fitness function is a measure to evaluate the performance of the SVM. The cross-validation objective is a verification method to verify the performance of the model. The process is to divide the original data into a training set and a verification set. After the training set is completed, the model is obtained by the verification set, and the prediction accuracy is obtained by testing the model as a regression index for evaluating the model. The area under the curve of ROC value is also one of the indexes for evaluating the classification effect of the model. In order to balance the influence of parameter selection on the model and reduce the possibility of algorithm over-learning, the sum of cross-validation and AUC weight is used as the fitness function.

\[
\text{fitness} = \frac{\varepsilon \sum_{i=1}^{k} MES_{i} + (1 - \varepsilon) \sum_{j=1}^{M \text{es}} \text{rank}_{j} - M(M + 1)/2}{M \times N}
\]

(21)

Where \( \varepsilon \) is the weight coefficient and \( 0 \leq \varepsilon \leq 1 \) and \( k \) are the number of data set divisions, from which one copy is drawn as a validation set, and the other \( k-1 \) copies are used as the training set, \( MES_{i} \) is the training error of each cycle model, and \( \sum_{j} \text{rank}_{j} \) is the serial number of all positive samples Sum, M, N is the number of positive and negative samples, \( \text{rank}_{j} \) is the sequence number of the \( j \)-th sample after sorting.

The steps of adaptive weight optimization particle swarm optimization are as follows:

Step1: Initialize the relevant parameters of the PSO and randomly generate the initial position of the particle within a certain range. The two components of the initial position of the particle are \( x(i,1) \) and \( x(i,2) \), that is, the two parameters corresponding to the SVM, namely the penalty factor C and the parameter g, where , The value range of \( x(i,1) \) is \( (C_{\text{min}}, C_{\text{max}}) \), and the value range of \( x(i,2) \) is \( (g_{\text{min}}, g_{\text{max}}) \).

Step2: Calculate the fitness value of the particles, and substitute the position components \( x(i,1) \) and \( x(i,2) \) of each particle into the fitness function to obtain the fitness value.
Step3: Determine the initial fitness value according to the particles, and obtain the individual extreme value $p_{\text{best}}$ and the group extreme value $g_{\text{best}}$ of the particle. Calculate the fitness variance of the population.

Step4: Update the adaptive weight of each particle according to formula (20).

Step5: Mutate some particles, generate a random number $R$ for each particle, $R$ obeys the normal distribution $N(0,1)$; combine $R$ with the mutation probability $g_{\text{best}}$ of the current particle swarm $P_g$, if $R > g_{\text{best}}$, then proceed as follows The mutation operation of formula (22), otherwise, it is not executed.

$$g_{\text{best}} = g_{\text{best}} (1 + R)$$ (22)

Step6: Determine whether the number of iterations is reached, if it is satisfied, then go to Step7, otherwise go to Step2.

Step7: Output the optimal position of the population, that is, the optimal SVM parameter.

4. Analysis of experimental results

4.1. Data Source

The human skin image collected by the CBS device is used as the data set for roughness classification and detection. After the device evaluation, there are 3 tags, and the total number of samples is 2688. After feature extraction, each sample has a total of 24 features. The data distribution under each label is shown in Table 1:

| Classification | Sample number | Feature number |
|----------------|---------------|----------------|
| 0              | 924           | 24             |
| 1              | 924           | 24             |
| 2              | 840           | 24             |

Each category of skin roughness random data set as a training set of 60%, remaining as a test set. In the training set to obtain the amount of cross-validation classification accuracy, selecting the highest average precision SVM combination of parameters, then the parameters for the test set to verify composition. The final classification accuracy rate is the classification accuracy of the data set.

4.2. Analysis of GA feature screening and optimization

After extracting the improved LBP-GLCM, Tamura feature, Fractal Dimension and Gabor feature from the above data set, each sample has a total of 24 features. In order to improve the classification performance of SVM and improve the correlation between features, genetic algorithm is used to optimize the above features.

Fig 3 Iteration diagram of genetic algorithm
From the fitness curve graph of the same dimension in 3(a), it can be seen that the genetic algorithm obtains the optimal chromosome fitness value from the fitness in the multi-dimensional number, and the feature takes 1-9 dimensions, and the fitness is shown after 9 dimensions. The downward trend of the value converges to around 1.01723. Therefore, the best 9-dimensional feature is selected from a large number of features as the training data of SVM; from Figure 2(b), it can be seen that when the 9-dimensional feature is selected, as the number of iterations increases, it finally converges to 3.81 after 40 iterations. Meet the expectations of the optimal dimension.

4.3 Result Analysis

For the adaptive particle swarm algorithm, the initial population iteration number is 100, the population size is 30, the learning factor $c1=c2=2$, the inertia weight $w_{\text{max}}=0.9$, $w_{\text{min}}=0.4$, the penalty factor range is $0.01 \leq C \leq 100$, and the kernel parameter range is $0.01 \leq g \leq 10$. Figure 4 shows the convergence of the particle fitness of the algorithm in the skin roughness dataset:

![Algorithm optimization fitness curve](image)

Fig 4 Algorithm optimization fitness curve

It can be seen from Fig. 4 that the optimal fitness of the particles under this algorithm starts to converge at iteration 15, and the overall average fitness also tends to converge, and it will be consistent with the optimal fitness after 80 generations. As shown in Figure 5, the fitness functions are the comparison results of cross-validation, AUC, and the fitness of this paper under the test set and the validation set. Compared with the values of cross-validation and AUC as fitness functions, the algorithm in this paper can achieve better results on the test set and the validation set.

![Algorithm optimization fitness curve](image)

Fig 5 Algorithm optimization fitness curve
Random forest, Adaboost algorithm, SVM algorithm, GA-SVM algorithm, PSO-SVM algorithm and the algorithm of this paper are used to compare the experimental results in accuracy, precision and recall rate:

| Algorithm    | Accuracy  | Precision | Recall Rate |
|--------------|-----------|-----------|-------------|
| Random forest| 0.902680  | 0.89264   | 0.90935     |
| Adaboost     | 0.95268   | 0.95253   | 0.95368     |
| SVM          | 0.95268   | 0.95157   | 0.95754     |
| GA-SVM       | 0.96488   | 0.963108  | 0.96472     |
| PSO-SVM      | 0.98511   | 0.98575   | 0.98513     |
| This Paper   | 0.99032   | 0.99426   | 0.99349     |

It can be seen from Tab 2 that the accuracy, precision and recall rate of SVM have been improved after GA feature screening. In the comparison of several algorithms such as random forest, the algorithm in this paper has advantages in the classification of skin roughness.

5. Conclusion
This paper proposes a multi-classification algorithm based on improved support vector machine for skin roughness. After dimensivity reduction of the original multi-dimensional eigenvalues of skin roughness images by using GA, the cross-validation classification accuracy and AUC are used together as the adaptive particle swarm fitness function to search for the optimal parameters. Finally the skin roughness image is established SVM multi-classification model. Numerical experiments show that substituting the optimized parameters into the model can significantly improve its classification performance. Compared with the classification effect of other classification algorithms, the classification support vector machine using adaptive particle swarm optimization kernel parameters has higher classification accuracy. However, when the adaptive particle swarm algorithm is used for parameter search, the increase of the iterative process will make the classification time too long, and the classification time will be optimized later.

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