Research of Thenar Palmprint Classification Based on Gray Level Co-occurrence Matrix and SVM

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Abstract—An optimal thenar palmprint classification model is proposed in this paper. Firstly, the thenar palmprint image is enhanced using a high-frequency emphasis filter and histogram equalization. Then, from the enhanced image thirteen textural features of gray level co-occurrence matrix (GLCM) are extracted as classification feature vectors. Finally, the SVM classifier is used for classification and the best classification model will be obtained through comparing the classification results of different kernel functions and feature vectors. The experimental results proved the feasibility and effectiveness of this model for thenar palmprint classification.

Index Terms—Gray Level Co-occurrence Matrix (GLCM), Support Vector Machine (SVM), High-frequency emphasis filter, histogram equalization, feature extraction, classifier

I. INTRODUCTION

According to long-term clinical practice, medical experts find that most of the allergic dermatitis and asthma (exogenous) patients have rough thenar palmprints. Through observing the direction, distance and depth of striae groove and striae and palpation information, they divide the thenar palmprints into the following four levels[1][2].

I: The surface skin of the thenar palmprints gloss, exquisite texture, the distance between two stria short, the depth of striae groove shallow, no characteristic patterns, soft palpation;

II: The surface skin of the big thenar palmprints gloss, texture clear and is shown as lattice-type distribution, but the distance of the stria is short, soft palpation;

III: The surface skin of the thenar palmprints lacks of gloss, texture clear and evident visible, Lattice-type distribution, the distance of the stria wide, soft palpation;

IV: The surface skin of the thenar palmprints dry and rough, texture clear, evident visible, palpable obstruction of hand, even palpable as the leather, shown as the big lattice-type distribution, the distance between two stria uniform and obviously wider than II level second grade.

We research the allergic dermatitis and asthma (exogenous) patient’s palmprints, and find that most of them have rough thenar palmprints. In order to make the classification of thenar palmprint more accurate, we use modern information processing method to identify the type of thenar palmprint rapidly an objectively.

Through using image processing method to analyses thenar palmprint, we find that the roughness of thenar palmprint can be represented by texture, so we use texture as the basis for classification. Texture is a kind of description about the spatial distribution of each pixel of an image. It can balance the macroscopic properties and detailed features better compared with other image features. Therefore, texture becomes an important extraction feature in target recognition [3]. There are many methods for texture feature extraction, including local statistical characteristics based feature, random field model based feature, spatial frequency based feature, fractal feature and so on. Among those the most widely used is the characteristics of Gray Level Co-occurrence Matrix based one (GLCM) [3-7].

Traditional learning machines such as the neural network is based on empirical risk minimization (EMR) principle which just minimizes the risk but not the mean error. This seriously hinders the method’s popularization. In 1995 Vapnik proposed a new learning method SVM based on structural risk minimization. This method has many unique advantages in solving small samples, nonlinear and high dimensional pattern recognition problems. Its stability and relatively high precision make it widely used. Statistic learning theory provides solid theoretical foundation for it.

In this paper we use SVM classifier for thenar palmprint classification and take the extracted features from GLCM as the classification feature vector. Through comparing the precision of different classifier with different kernel function, we proposed an optimal model for thenar palmprint classification.

II. IMAGE ENHANCEMENT WITH HIGH-FREQUENCY EMPHASIS FILTER AND HISTOGRAM EQUALIZATION

The thenar palmprint is obtained by segmenting the original image to get the interested region. The image
enhancement is conducted by high-frequency emphasis filter combined with histogram equalization. Through enhancing the regions and edges of brightness changes, high-frequency emphasis filter makes the image clearer in texture. However, current high-pass filters deviate from the origin of Fourier transform, which makes the original color image lose most of the background. A compensation method is to add an offset to a high-pass filter. The high-frequency emphasis filter is the offset add to a high-pass filter multiplied by a constant greater than 1.

The constant multiplier gives prominence to the high-frequency part and it also increases the low-frequency range, but as long as the offset is smaller than the constant multiplier, the impact on low-frequency enhancement is weaker than high-frequency enhancement.

The function of the high-frequency emphasis filter is:

\[ H_{hp}(u,v) = a + bH_{lp}(u,v) \]

Where \( a \) is offset, \( b \) is the constant multiplier, \( H_{lp}(u,v) \) is the high-pass filter function.

Histogram equalization is through

\[ T(r) = \int_0^r P_r(w)dw \]

which is an cumulative distribution function accumulating the normalized original image, \( P_r(w) \) is the probability density function. The processing result is an image with high contrast and extended dynamic range.

III. GRAY LEVEL CO-OCCURRENCE MATRIX

Gray level co-occurrence matrix is an important texture feature in image analysis [3-6]. Suppose an image is rectangular and has \( N_x \) resolution cells in the horizontal direction and \( N_y \) resolution cells in the vertical direction, and the gray tone appearing in each resolution cell is quantized to \( N_g \) levels. Let \( L_x = \{1,2,...,N_x\} \) be the horizontal spatial domain, \( L_y = \{1,2,...,N_y\} \) be the vertical spatial domain, and \( G = \{1,2,...,N_g\} \) be the set of \( N_g \) quantized gray tones. The set \( L_x \times L_y \) is the set of resolution cells of the image ordered by their row-column designations. The image \( I \) can be represented as a function which assigns some gray tones in \( G \) to each resolution cell or pair of coordinates in \( L_x \times L_y \); that is \( L_x \times L_y \subset G \).

An essential component of our conceptual framework of texture is a measure, or more precisely, four closely related measures from which all of four texture features are derived. These measures are arrays termed angular nearest-neighbor gray-tone spatial-dependence matrix, and to describe these arrays we must emphasize our notion of adjacent or nearest-neighbor resolution cells. Now consider a resolution cell, excluding those on the periphery of an image. Each resolution cell has eight nearest-neighbor resolution cells as shown in Fig.1.

<table>
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<tr>
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<th>90 degree</th>
<th>45 degree</th>
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<tr>
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<tr>
<td>4</td>
<td>3</td>
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</table>

Figure 1. Eight nearest-neighbor resolution

Resolution cells 1 and 5 are 0 (horizontal) nearest neighbors to resolution cell *, resolution cells 2 and 6 are 135 degrees nearest neighbors; resolution cells 3 and 7 are 90 degrees nearest neighbors; and resolution cells 4 and 8 are 45 degrees nearest neighbors to *

We assume that the texture information is adequately specified by the matrix of relative frequency \( P_{ij} \), with which two neighboring resolution cells separated by distance \( d \) occur on the image, one with gray tone \( i \) and the other with gray tone \( j \). The matrix of GLCM is defined as a function of the angles and distance between the neighboring resolution cells. Generally, the angles are quantized to 45° intervals and the un-normalized frequencies are defined as follows [6]:

\[ P_{ij,d,00} = \# \{(k,l),(m,n) \in (L_y \times L_x) \times (L_y \times L_x) | \begin{align*} k-m=0, & \ l-n=0, \ i=k, l=m=j; \\ k-m=d, & \ l-n=-d, \ i=k, l=m=j; \\ k-m=-d, & \ l-n=d, \ i=k, l=m=j; \end{align*} \]

\[ P_{ij,d,450} = \# \{(k,l),(m,n) \in (L_y \times L_x) \times (L_y \times L_x) | \begin{align*} k-m=d, & \ l-n=-d, \ i=k, l=m=j; \\ k-m=-d, & \ l-n=d, \ i=k, l=m=j; \end{align*} \]

\[ P_{ij,d,900} = \# \{(k,l),(m,n) \in (L_y \times L_x) \times (L_y \times L_x) | \begin{align*} k-m=d, & \ l-n=-d, \ i=k, l=m=j; \\ k-m=-d, & \ l-n=d, \ i=k, l=m=j; \end{align*} \]

Where \# denotes the number of elements in each set.

Consider Fig.2(a), which represents a 4 × 4 image with four gray tones, ranging from 0 to 3. Fig.2(b) shows the general form of any GLCM. For example, the element in the (2,1) position of the distance 1 horizontal \( P_{ij} \) matrix is the total number of times two gray tones of value 2 and 1 occurred horizontally adjacent to each other. To determine this number, we count the number of pairs of resolution cells in \( R_H \) such that the first resolution cell of the pair has gray tone 2 and the second resolution cell of the pair has gray tone 1. In Fig.2(c)-(f) we calculate all of four distance 1 gray level co-occurrence matrices.
Figure 2. The gray level co-occurrence matrix of a 4 × 4 image with four gray-level values 0-3.

We assume that all the texture information is contained in the GLCM. Hence all the textural features we suggest are extracted from GLCM, 13 texture features are defined as follows[3]:

\[ R_{jiP} = \sum_{g=1,2,3,2} \sum_{x=0,1,2,3} \sum_{y=0,1,2,3} N_{x,y} \]

\[ P_{ij} = \begin{bmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 2 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix}, \quad P_{ij} = \begin{bmatrix} 6 & 0 & 2 & 0 \\ 0 & 4 & 2 & 0 \\ 2 & 2 & 2 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix} \]

\[ P_{ij} = \begin{bmatrix} 2 & 1 & 2 & 0 \\ 1 & 2 & 1 & 0 \\ 2 & 1 & 0 & 2 \\ 0 & 0 & 2 & 0 \end{bmatrix}, \quad P_{ij} = \begin{bmatrix} 4 & 1 & 0 & 0 \\ 1 & 2 & 2 & 0 \\ 0 & 2 & 4 & 1 \\ 0 & 0 & 1 & 0 \end{bmatrix} \]

\[ f_2 = \sum_{n=0}^{N_x-1} h^n \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \{P(i,j)\} \]

3) Correlation

\[ f_3 = \frac{\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} (ij)P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \]

Where \( \mu_x, \mu_y, \sigma_x, \sigma_y \) are the means and standard deviations of \( P_x \) and \( P_y \).

4) Sum of Squares : Variance

\[ f_4 = \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} (i - \mu)^2 P(i,j) \]

5) Inverse Different Moment

\[ f_5 = \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \frac{p(i,j)}{1 + (i - j)^2} \]

6) Sum Average

\[ f_6 = \sum_{i=2}^{2N_x} iP_{x+y}(i) \]

7) Sum Variance

\[ f_7 = \sum_{i=2}^{2N_x} (i - f_6)^2 P_{x+y}(i) \]

8) Sum Entropy

\[ f_8 = -\sum_{i=2}^{2N_x} P_{x+y}(i) \log\{P_{x+y}(i)\} \]

9) Entropy

\[ f_9 = -\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} P(i,j) \log\{P(i,j)\} \]

10) Difference Variance

\[ f_{10} = \sum_{i=0}^{N_x-1} (i - \mu)^2 P_{x+y}(i) \]

11) Difference Entropy

\[ f_{11} = -\sum_{i=0}^{N_x-1} P_{x-y}(i) \log\{P_{x-y}(i)\} \]

Information Measures of Correlation

\[ f_{12} = \frac{HXY - HXY1}{\max\{HX, HY\}} \]

13) \( f_{13} = (1 - \exp[2.0(HXY2 - HXY)])^{1/2} \)

\[ HXY = -\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} P(i,j) \log\{P(i,j)\} \]

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\[ HXY_1 = -\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} P(i, j) \log \{P_x(i)P_y(j)\} \]
\[ HXY_2 = -\sum_{i=1}^{N_x} \sum_{j=1}^{N_y} P_x(i)P_y(j) \log \{P_x(i)P_y(j)\} \]

where \( HX \) and \( HY \) are entropies of \( P_x \) and \( P_y \).

\[ HX = -\sum_{i=1}^{N_x} P_x(i) \log \{P_x(i)\} \]
\[ HY = -\sum_{i=1}^{N_y} P_y(i) \log \{P_y(i)\} \]

IV. SUPPORT VECTOR MACHINE

SVM (support vector machine) is a new machine learning method proposed by Vapnik etc., which is based on structural risk minimization. It has also been proved to be very successful in many other applications such as handwriting figures recognition, image classification, face detection, object detection, text classification [12-15], etc. The statistical learning theory becomes more and more popular with this general method’s emergence.

The traditional machine learning is based on average risk minimization, but usually we only know some information about independent samples. Therefore the average risk can’t directly be calculated. According to the idea law of large numbers in probability theory, we can use the empirical risk to calculate the independent samples approximating the average risk. That is empirical risk instead of average risk. The capacity of the machine predicting the correct future output is called generalization performance. In the early neural network research, people always focus on how to minimize the empirical risk, but they soon discovered that only minimizing the empirical risk couldn’t get good predict result. Under the condition of limited samples, high accuracy and generalization performance are a pair of irreconcilable contradictions. With complex machine learning method we can obtain smaller error, but meanwhile the generalization performance will become lower. In order to solve this problem, statistical theory put forward a concept of VC dimension. The VC dimension is a property of a set of functions and can be defined for various classes of function, therefore we only consider functions that correspond to two-classes pattern recognition. The VC dimension for the set of function \( f \) is defined as the maximum number of training points which can be shattered by \( f \). It reflects the learning ability of the set of function \( f \). The larger the VC dimension is, the stronger learning ability, the more complex of the machine and the worse generalization performance.

The process of machine learning is under the condition of minimization of the empirical risk to make the VC dimension smallest. The principle of SVM is that giving some selection of learning machines whose structural risk error is less than the bottom line of the given error.

A. SVM Binary Classification Algorithm

For two linear separable class samples \((x_i, y_i), i = 1, \cdots, N, x \in R^2, y \in \{+1, -1\}\), where \( N \) is the total of the training samples, \( n \) is the space dimension of the samples, \( y \) is the class sign of the samples.

![Figure 3. The figure of the Optimal Hyper-Plane](image)

Figure.3 is a two class linear separable hyper-plane, \( H \) is the optimal hyper-plane which equation is \( wx + b = 0 \). The optimal hyper-plane not only separates two classes, but also makes the classification interval largest, which controls the generalization performance. Therefore, minimizing \( ||w|| \) makes the confidence interval smallest, and \( 2/||w|| \) largest. This shows that the maximum interval can be transformed into the \( ||w|| \) minimization problem. In linear separable case, the principle of structural risk minimization optimal separating hyper-plane can be obtained by minimizing the function:

\[ \Phi(w) = \frac{1}{2}||w||^2 = (w \cdot w) \]

Because the hyper-plane classifies all data and the nearest sample points to hyper-plane satisfying \( \|f(x)\|=1 \), so the hyper-plane constrains as follows:

\[ y_i(x_i \cdot w + b) \geq 1, i = 1, \cdots, N \]

Then, the Lagrangian function is defined as follows:

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

Where \( \alpha_i > 0 \) is the Lagrangian coefficient, we seek the minimum value of \( w \) and \( b \) in the above equation. Through respectively partial derivative of \( w \) and \( b \), and making them equal to 0, the original problem can be transformed into relatively simple dual problem, constraints as:

\[ \sum_{i=1}^{N} y_i \alpha_i = 0, \alpha_i \geq 0, i = 1, \cdots, N \]

Seek the maximum value of the following functions whose parameter is \( \alpha_i \)
If $\alpha^*$ is the optimal solution, then

$$w^* = \sum_{i=1}^{N} \alpha_i^* y_i x_i$$

According to Kuhn-Tucke conditions, the optimal solution must meet with this equation:

$$\alpha_i (y_i (w \cdot x_i + b) - 1) = 0, i = 1, \ldots, N$$

Where $\alpha_i$ is the support vector coefficient, we can obtain $b$ by substitution $w$ with $w^*$ in the above equation, and then the optimal classification function is got:

$$f(x) = \text{sgn}\{w^* \cdot x + b\} = \text{sgn}\{\sum_{i=1}^{N} \alpha_i^* y_i (x_i \cdot x) + b\}$$

As to non-linear separate case, samples can be mapped through a nonlinear function $K(x_i \cdot x_j)$ to high dimension feature space which is linearly separable. The optimal hyper-plane in this feature space is set up. Using $K(x_i \cdot x_j)$ instead of dot product in optimal classification plane, the original feature space is transformed into a new feature space and the optimal function is as follows:

$$Q(\alpha) = \sum_{i=1}^{N} \alpha_i - 1/2 \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j)$$

The corresponding classification function is:

$$f(x) = \text{sgn}\{\sum_{i=1}^{N} \alpha_i^* y_i K(x_i \cdot x) + b\}$$

Other conditions of the algorithm remain unchanged. The choice of the kernel function $K(x_i \cdot x_j)$ must satisfy the Mercer conditions. Different forms of kernel functions determinate different support vector machine, currently there’re mainly three kinds [11]:

1) $q$-order polynomial function

$$K(x_i, x_j) = (x_i \cdot x_j + 1)^q$$

At this point, the SVM is a $q$-order polynomial classifier.

2) RBF kernel function

$$K(x_i, x_j) = \exp\left\{-\frac{||x_i - x_j||^2}{\sigma^2}\right\}$$

The SVM is a RBF kernel function classifier. Its fundamental difference from neural network approach is that the center of each kernel function corresponds to a vector while the structure and weights of the neural network are determined by the algorithm automatically.

3) Sigmoid kernel function

$$K(x_i, x_j) = \tanh(c_1 (x_i \cdot x_j) + c_2)$$

V. CLASSIFICATION MODEL

A suitable model for thenar palmprint classification is proposed on the basis of the above analysis. It falls into three steps: image enhancement filter to enhance the texture; feature extraction; and SVM classifier design.

In order to classify thenar palmprints, according to Traditional Chinese medicine experts knowledge, the thenar palmprint is divided into two categories: the positive thenar palmprint have roughness vein, and the negative thenar palmprint have not significant vein. The following experimental images are negative 1st and positive 3rd.

A. Image enhancement filter

Select the parameters of the image enhancement filter $a=0.5, b=2$, the high pass filter is Butterworth filter. The original image and the processed image are shown in Figure 4:

(a) 1st level original image       (b) 3rd level original image

Figure 4. The original thenar palmprint image
the experiment results show that this method is effective.

Because the contrast of the original image is not high, and the high-frequency filter can enhance the high frequency components by increasing the multiplicative coefficient, the experiment results show that this method is effective.

B. Features extraction of GLCM

Generally, the gray level of a gray image is 256, but in calculating the texture features of GLCM, the required gray level is far less than 256. When the matrix dimension is larger and the window size is small, GLCM will not represent the texture well. A good texture representation requires a larger window size, meanwhile, the computation will increase. And when the window becomes larger, the error rate of the boundaries region for each category is higher. Therefore, before calculating the GLCM, the image needs to be quantified to reduce the image’s gray level. Generally the quantitative gray-level is 8 or 16. Here we make the quantization gray-level 16.

For the above two images, select $d=1$, $A=(0^{\circ} 45^{\circ} 90^{\circ} 135^{\circ})$. 13 texture features are extracted from GLCM as shown in the following table.

### TABLE I.
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<th>F A</th>
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<th>f3</th>
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C. SVM classifier design

The raw data is scaled to (-1,+1) before the SVM training process. Various types of SVM classifier can be obtained from the training data and the trained classifier can be verified using the test data. The appropriate classification model is selected according to the accuracy requirement.

In order to select the best SVM model for the thenar palmprint classification, we have made a lot of experiments. Searching the penalty factor from 1:1:100, we got the optimal penalty factor $C=27$, and the polynomial kernel function with $q=1$ is the best kernel function. TableII can prove the conclusion. At the same time, the combination feature vectors have higher accuracy rate, which is the result of combining the four directions feature vectors to get the final feature vector of the training data. This feature vector dimension is 50×42 and the SVM classifier is got by training these feature vectors.

VI. EXPERIMENTAL RESULTS ANALYSIS

We have acquired 400 experimental images with identification by medical experts, each level have 100, that is the positive thenar palmprints is 200, negative thenar palmprints is 200. There are 50 training samples and 50 testing samples in every level for experiments.

The results of SVM binary classification results are shown in TABLE III.
In multi-classification the feature vector is Feature (0,45,90,135) and the kernel function is polynomial function.

![Table III](image)

Table III: Experimental results of binary classification

<table>
<thead>
<tr>
<th>Feature vector</th>
<th>poly</th>
<th>rbf</th>
<th>Sigmoid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feature0</td>
<td>75.5%</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>Feature45</td>
<td>64.8%</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>Feature90</td>
<td>65.8%</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>Feature135</td>
<td>69.5%</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>Feature 0, 45, 90, 135</td>
<td>87.5%</td>
<td>50%</td>
<td>50%</td>
</tr>
</tbody>
</table>

From the above experimental results we can see that using the method proposed in this paper the accuracy rate for binary classification of thenar palmprint is 87.5%, while using decision tree SVM multi-classification, the result is not ideal. The reason lies in several aspects. Firstly, there is a considerable level of subjective factors when medical experts determine the level of thenar palmprint. Because the boundaries between 1, 2 and 3, 4 are fuzzy, the binary classification accuracy rate is higher than multi-classification. Secondly, the increase of training samples can improve the accuracy of classification to some extent.

VI. CONCLUSIONS

In this paper, the gray level co-occurrence matrix theory and support vector machine method are depicted. Different directions feature vectors are obtained through thenar palmprint’s GLCM. Firstly, The SVM is used for binary classification. Experimental results show that different features have different precision, and the combination of variable features can get higher classification accuracy. The results show that the decision tree SVM multi-classification based on SVM binary classification is not very satisfactory. If samples can be screened further or the number of samples is increased, the accuracy rate of classification can be improved. Experimental results show that the model we have established is accurate and effective for preliminary classification of thenar palmprint, and provide a basis for further refined classification.

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REFERENCE


