Postprint of Color Palmprint Feature Recognition Algorithm Based on Stein-Weiss Function

Authors: Wu Mingzhu, Chen Ying, Xingmin Li

Date: 2019-04-01T00:00:00+00:00

Abstract

Given the limited research on color palmprint image recognition in existing palmprint recognition algorithms, this paper proposes a novel color palmprint image recognition algorithm based on the analytic properties of Stein-Weiss functions using BP neural networks. First, a Stein-Weiss function is constructed for each pixel in the color palmprint image. Then, based on the analyticity of the Stein-Weiss function, sixteen feature values corresponding to each pixel are calculated. These feature values are fed into the input layer of the BP neural network, which performs classification learning on this data through its self-learning capability. Subsequently, the generalization capability of the BP neural network is leveraged to extract palmprint edge lines. Finally, pairwise geometric features are extracted from the palmprint edge lines to establish a feature library, and palmprint recognition is accomplished using a pairwise geometric histogram intersection algorithm. Experimental results demonstrate that, compared with previous grayscale palmprint image recognition algorithms, this algorithm can extract finer palmprint lines more rapidly, achieves higher recognition rates, and exhibits strong robustness against rotation and noise interference.

Full Text

Preamble

Vol. 37 No. 5
Application Research of Computers
ChinaXiv Cooperative Journal
Accepted Paper

Color Palmprint Feature Recognition Algorithm Based on Stein-Weiss Function

Wu Mingzhu[1], Chen Yin[1], Li Xingmin[2]
(1. Dept. of Information Engineering, Guangzhou Institute of Technology,

Guangzhou 510075, China;
2. School of Computer, South China Normal University, Guangzhou 510631, China)

Abstract: Current palmprint recognition algorithms have devoted limited research to the recognition of color palmprint images. To address this gap, this paper proposes a novel BP neural network color palmprint image recognition algorithm based on the analytical properties of Stein-Weiss functions. The method first constructs a Stein-Weiss function for each pixel in the color palmprint image. Based on the analyticity of the Stein-Weiss function, sixteen eigenvalues are calculated for each corresponding pixel. These eigenvalues serve as input to the BP neural network' s input layer, where they are classified and learned through the network' s self-learning capability. The palmprint edge lines are then obtained via the generalization ability of the BP neural network. Finally, pairwise geometric features are extracted from the palmprint edge lines to establish a feature library, and palmprint recognition is performed using a paired geometric histogram intersection algorithm. Experimental results demonstrate that compared with previous grayscale palmprint image recognition algorithms, the proposed algorithm can extract finer palmprint lines more rapidly, achieves higher recognition rates, and exhibits stronger robustness against rotation and noise interference.

Keywords: Stein-Weiss function; analyticity; backpropagation neural network; palmprint recognition; pairwise attributes; robustness

Classification: TP391.41
doi: 10.19734/j.issn.1001-3695.2018.10.0845

0 Introduction

Palmprint recognition is a biometric identification technology. Compared with other biometric features such as fingerprints and faces, palmprints offer a relatively larger area containing more personal information, exhibit rotation invariance and uniqueness, and benefit from low-cost acquisition devices. In recent years, palmprint recognition has been widely applied in scientific and technological fields, demonstrating promising application prospects.

The complete palmprint recognition algorithm process primarily includes palmprint image acquisition, image preprocessing, palmprint feature extraction, and feature matching and recognition. Commonly used palmprint feature extraction algorithms mainly consist of: (1) Structure-based extraction algorithms that rely on point and line structural features. This approach is straightforward and easy to understand, but extraction results depend heavily on edge detection and preprocessing effectiveness, often leading to loss of detail. (2) Texture-based extraction algorithms that utilize palmprint texture energy for description, reducing computational complexity but suffering from stability issues under changing illumination conditions. (3) Subspace-based extraction algorithms that transform from high-dimensional to low-dimensional space, offering strong feature description capabilities and high recognition rates, but potentially causing singularity in the within-class scatter matrix.

Common palmprint matching and recognition algorithms mainly include Euclidean distance, Hamming distance, BP neural networks, and support vector machine classification methods.

Most of the aforementioned palmprint extraction and recognition algorithms are based on grayscale palmprint images. However, color palmprint images contain richer information than grayscale images. Direct feature extraction from color palmprint images can obtain more personal information, which is more beneficial for biometric identification work. The development of high-dimensional mathematical theory in recent years has provided advantageous tools for directly extracting features from color images. Reference [?] utilized quaternions for edge detection and extraction in color images, marking the beginning of applying hypercomplex numbers to color image research. Reference [?] proposed using the Clifford algebra vector product representation theorem to extract palmprint lines, but this was not performed directly on color images. Reference [?] presented a color image automatic extraction algorithm based on the octonion vector product representation theorem, with experimental results demonstrating the ability to extract relatively fine palmprint lines with high recognition rates.

Building upon the research in [?], this paper proposes an improved palmprint recognition algorithm. Stein-Weiss analytic functions represent high-dimensional function theory, and palmprint images exhibit multi-directional characteristics, providing a suitable high-dimensional mathematical tool for palmprint recognition research. Moreover, compared with octonions, which are also high-dimensional mathematical theories, Stein-Weiss functions offer better analyticity [?]. Therefore, to extract finer palmprint lines, this paper proposes a BP neural network color palmprint image recognition algorithm based on the analytic properties of Stein-Weiss functions.

1 Stein-Weiss Analytic Functions

Stein and Weiss generalized analytic functions in high-dimensional Hardy spaces by introducing the following definition of Stein-Weiss analytic functions [?]. Let F be a vector function set in region R^n. If F is the gradient of a real harmonic function in this region, then F is called a Stein-Weiss analytic function in this region, also known as a conjugate harmonic function system [?].

The function satisfies the generalized Cauchy-Riemann equations [?]:

$$\sum_{j=0}^{n} \frac{\partial u_j}{\partial x_j} = 0, \quad \frac{\partial u_i}{\partial x_j} = \frac{\partial u_j}{\partial x_i}$$

When $n = 2$, $F = u + iv$ is analytic if and only if (u, v) is a Stein-Weiss analytic function.

Theorem [?]: Let F be a Stein-Weiss analytic function, then F is both left and right H-analytic.

2 BP Neural Network

The BP neural network using error backpropagation algorithm involves two learning processes [?]. The first is forward signal propagation: input signals are processed through hidden layers to output layer nodes, undergoing nonlinear transformation to produce the actual output values for each output layer node. The second process propagates output errors backward: if the actual output values do not match the desired outputs, errors are backpropagated layer-by-layer from the output layer through hidden layers to the input layer, recursively calculating errors and cyclically adjusting weights based on these errors. This constitutes the cyclic training process of neural network learning [?].

2.1 Forward Propagation Process

Define the BP neural network as net_{BP} with input vector $A = (a_1, a_2, \dots, a_k)$, sample input vector $S = (s_1, s_2, \dots, s_p)$, hidden layer input vector $B = (b_1, b_2, \dots, b_p)$, hidden layer output vector $C = (c_1, c_2, \dots, c_p)$, output layer input vector $L = (l_1, l_2, \dots, l_q)$, and output vector $Y = (y_1, y_2, \dots, y_q)$. Let m be the number of samples, n the number of input layer nodes, p the number of hidden layer nodes, and q the number of output layer nodes [?]. The weights from input to hidden layer are w_{ij}, and from hidden to output layer are v_{jt}. The hidden layer thresholds are θ_j, and output layer thresholds are γ_t.

Hidden layer output:

$$c_j = f\left(\sum_{i=1}^{n} w_{ij} a_i - \theta_j\right), \quad j = 1, 2, \dots, p$$

Output layer input:

$$l_t = \sum_{j=1}^{p} v_{jt} c_j - \gamma_t, \quad t = 1, 2, \dots, q$$

Output layer output:

$$y_t = f(l_t), \quad t = 1, 2, \dots, q$$

2.2 Error Backpropagation Process

Output errors are backpropagated layer-by-layer from hidden layers to the input layer. During this process, errors decrease along the gradient direction, and weights and thresholds corresponding to minimum error are determined through repeated training and learning [?].

This approach represents the standard error backpropagation algorithm. However, if all global errors from learning samples are input to the network before uniformly adjusting connection weights, this constitutes the cumulative error backpropagation algorithm [?]. This paper uses global error, calculated as follows:

$$E = \sum_{k=1}^{m} E_k$$

The weight adjustment from hidden to output layer is:

$$\Delta v_{jt} = -\alpha \frac{\partial E}{\partial v_{jt}} = \alpha \delta_t c_j$$

The output layer threshold adjustment is:

$$\Delta \gamma_t = -\alpha \frac{\partial E}{\partial \gamma_t} = -\alpha \delta_t$$

The weight adjustment from input to hidden layer is:

$$\Delta w_{ij} = -\beta \frac{\partial E}{\partial w_{ij}} = \beta e_j a_i$$

The hidden layer threshold adjustment is:

$$\Delta \theta_j = -\beta \frac{\partial E}{\partial \theta_j} = -\beta e_j$$

2.3 Memory Training

After inputting a set of samples into the network, repeated learning training is performed. Network parameters (weights and thresholds) are adjusted to control actual output values within specified ranges.

2.4 Learning Convergence

The network's global error tends toward a minimum value after multiple training iterations. During training, to avoid converging to local minima, this paper adds a small random number to each weight and appropriately varies the number of hidden layer units.

3 Color Palmprint Extraction Algorithm Based on Stein-Weiss Analyticity and BP Neural Network

Since palmprint distributions in two-dimensional color palmprint image data are mostly vertical or oblique, this algorithm comprehensively considers structural features of image pixels in both oblique and vertical directions, employing a six-neighborhood structure. Feature values obtained based on Stein-Weiss function analytic properties are then input into the BP neural network input layer for repeated training, ultimately producing color image palmprint line extraction results. The specific algorithm steps are as follows:

a) Automatic acquisition of BP neural network training samples. Following the method proposed in [**?**], four traditional edge detection operators are used to extract edge images from palmprint sample images. These are then fused via logical OR operation and dilated. The dilated palmprint edge image serves as training samples for the BP neural network [**?**]. Input sample vectors are trained until the error reaches a set threshold, at which point weights and thresholds are saved. Experimental results are shown in Figure 1, where (a) is the original palmprint image and (b) is the fused and dilated edge image used as network training samples.

[Figure 1: see original paper]

b) Definition of pixel Stein-Weiss functions. Define a six-dimensional vector space vector function as:

$$f(x) = f_0 + f_1 e_1 + f_2 e_2 + f_3 e_3 + f_4 e_4 + f_5 e_5 + f_6 e_6$$

where $(x_1, x_2, x_3, x_4, x_5, x_6)$ are pixel coordinates, and $f_1, f_2, f_3, f_4, f_5, f_6$ are the R, G, B, H, S, I component values of color palmprint image pixels, respectively, as shown in Figure 2 [Figure 2: see original paper].

c) Feature value acquisition. Substitute the vector function $f(x)$ into the generalized Cauchy-Riemann equations and apply difference operations. Since actual image analyticity may not perfectly conform to these formulas, according to the Stein-Weiss function analyticity theorem, an appropriate threshold T is used to determine whether a pixel satisfies analyticity. As edge points do not satisfy analyticity, equations (12) and (13) are rewritten as:

$$\sum_{j=0}^{6} \frac{\partial f_j}{\partial x_j} = 0, \quad \frac{\partial f_i}{\partial x_j} = \frac{\partial f_j}{\partial x_i}$$

Expanding equations (14) and (15) yields a_i and b_{ij}, where $i, j = 0, 1, \dots, 5$ and $i \neq j$. These 16 values serve as the 16 feature values of the image.

d) Palmprint edge line extraction. Select the color palmprint image to be recognized and extract its feature values. These 16 values are input into the BP network input layer, so the input layer has 16 nodes. The network trained in step a) is used to train the input vector until the error converges to a specified value. The final output is the palmprint extraction result. The output is a binary image, so the output layer has 2 nodes. This paper sets the number of hidden layer units to 8.

4 Palmprint Matching Algorithm Based on Pairwise Geometric Feature Histograms

After extracting edges from color palmprint images using the improved algorithm, the next critical task is palmprint recognition based on these extracted edge features. This paper utilizes pairwise geometric features with geometric invariance properties [?]—namely oriented relative angles and oriented relative positions—to establish a feature library, and employs a pairwise geometric feature histogram intersection algorithm for image matching and recognition.

4.1 Construction of Pairwise Geometric Feature Vectors

This paper combines Stein-Weiss analyticity with BP neural networks to extract color palmprint edges, producing binary images. First, an improved Hough transform algorithm from [?] is applied to extract linear features from the binary images. Pairwise geometric features (oriented relative angles and oriented relative positions) [?] are then introduced to construct palmprint edge feature vectors, as shown in Figure 3 [Figure 3: see original paper].

1) Construction of oriented relative angle feature vectors
Represent any two line segments as vectors $\vec{ab}$ and $\vec{cd}$ with directions pointing away from their intersection point. The oriented relative angle feature formula is [?]:

$$\theta_{ij} = \arccos\left(\frac{\vec{ab} \cdot \vec{cd}}{|\vec{ab}| \cdot |\vec{cd}|}\right)$$

If the angle direction between two line segments is clockwise, the oriented relative angle sign is positive; otherwise, it is negative.

2) Construction of oriented relative position feature vectors
The oriented relative position feature formula is [?]:

$$\mathcal{D}_{ij} = \frac{1}{2}\left(\frac{\vec{ab}}{|\vec{ab}|} + \frac{\vec{cd}}{|\vec{cd}|}\right) \cdot \vec{D}_{ab,cd}$$

4.2 Construction of Pairwise Geometric Feature Histograms

After constructing the pairwise geometric feature vectors, two-dimensional feature histograms are used for convenient matching. The formula for calculating two-dimensional histogram bins is [?]:

$$H(i,j) = \begin{cases} 1 & \text{if } (\theta_{ij}, \mathcal{D}_{ij}) \in E \\ 0 & \text{otherwise} \end{cases}$$

where i and j represent two line segments extracted from the palmprint edge image, and E represents the edge set.

4.3 Histogram Intersection Matching Algorithm [?]

For convenient matching, the two-dimensional feature histogram from Section 4.2 is scanned row-wise and reduced to a one-dimensional histogram. Two histograms A and B corresponding to two palmprint images are normalized to obtain n bins. The distance between two histograms is calculated using:

$$d = 1 - \sum_{i=1}^{n} \min(A_i, B_i)$$

The d value ranges in $[0, 1]$, with its magnitude determining image similarity—smaller values indicate greater similarity.

5 Experimental Results and Analysis

Experiments were conducted on a Windows 7 system using Visual Studio and MATLAB 7.0 programming tools. To verify effectiveness, 60 individuals were collected, with 4 color palmprint images per person as the sample set, all sized 128×128. These samples were processed using the proposed color palmprint feature extraction and matching algorithm for palmprint edge feature extraction and pairwise geometric feature histogram construction, thereby establishing a color palmprint feature library.

5.1 Color Palmprint Line Extraction Experimental Results Analysis

Seven algorithms were compared for color palmprint edge extraction: four traditional operators (Canny, Robert, Sobel, and Prewitt), quaternion analyticity combined with BP neural network from [?], octonion analyticity BP neural network from [?], and the proposed Stein-Weiss analyticity BP neural network. Results are shown in Figure 4 [Figure 4: see original paper].

Since the four traditional edge extraction operators require conversion of color palmprint images to grayscale before extraction, this process already loses partial information. The experimental results show that palmprint edges extracted using traditional operators (Figures 4(c)-(f)) contain significantly less edge information compared to Figures 4(b), (g), and (h).

Quaternions, octonions, and the proposed Stein-Weiss analytic functions can directly extract edges from color palmprint images. Comparing these three algorithms, the quaternions analyticity combined with BP neural network (Figure 4(g)) produces palmprint edges with less abundant and clear information than the other two algorithms (Figures 4(b) and (h)). Comparing Figures 4(b) and (h), the proposed algorithm extracts finer palmprint details than the octonion analyticity BP neural network algorithm—details circled in red in Figure 4(b) are less clear at the same positions in Figure 4(h).

5.2 Color Palmprint Line Recognition Experimental Results Analysis

1) Overall performance test of recognition algorithm

The proposed palmprint feature extraction and recognition algorithm, the octonion-based color palmprint feature extraction and recognition algorithm from [?], and the convolutional neural network palmprint recognition algorithm from [?] were used to match and recognize images from the established feature libraries using the sample image in Figure 4(a). Performance comparisons are shown in Table 1 .

Table 1 Comparison of recognition performance between three algorithms

Algorithm	False Rejection Rate (%)	False Acceptance Rate (%)	Recognition Success Rate (%)	Average Runtime (s)
Proposed Algorithm	0	0	98.75	1.2
Algorithm from [?]	0	0	95.83	1.5
Algorithm from [?]	0	0	99.17	8.5

The data in Table 1 shows that compared with the algorithm from [?], the proposed algorithm achieves higher recognition success rates and operational efficiency. This is because Stein-Weiss analyticity is superior to octonion analyticity, and more feature value vectors are input, resulting in richer extracted edge information.

Although the recognition rate of [?] is slightly higher than the proposed algorithm, convolutional networks require significantly longer training time, resulting in much greater overall runtime. Therefore, considering both recognition rate and runtime, the proposed algorithm outperforms the convolutional neural network recognition algorithm.

2) Robustness test of recognition algorithm

The matching and recognition process uses pairwise geometric features based on geometric invariance properties, demonstrating high robustness to rotation variations and noise interference. Specific experimental tests are as follows.

First, the test original image Figure 4(a) was rotated counterclockwise by 30°, 45°, and 60°, as shown in Figures 5(a)-(c) [Figure 5: see original paper].

[Figure 5: see original paper]

The proposed algorithm, the octonion-based algorithm from [?], and the convolutional neural network algorithm from [?] were used to match and recognize images from their respective feature libraries using Figures 5(a)-(c) as sample images. Performance comparisons are shown in Table 2 .

Table 2 Comparison of recognition performance between three algorithms for rotational robustness

Algorithm	30° Rotation	45° Rotation	60° Rotation
Proposed Algorithm	97.92%	96.67%	95.83%
Algorithm from [?]	89.58%	87.50%	85.42%
Algorithm from [?]	98.33%	97.50%	96.67%

Table 2 data shows that compared with [?], both the proposed algorithm and [?] demonstrate far superior rotational robustness. However, although [?] achieves higher recognition rates, Table 1 already shows that convolutional neural network recognition algorithms require substantial training time.

Additionally, different levels of Gaussian noise interference were added to test original image Figure 4(a), as shown in Figures 6(a)-(b) [Figure 6: see original paper] with parameters $\mu = 0, \sigma = 0.001$ and $\mu = 0, \sigma = 0.005$.

[Figure 6: see original paper]

The three algorithms were used to match and recognize images from their feature libraries using Figures 6(a)-(b) as sample images. Performance comparisons are shown in Table 3 .

Table 3 Comparison of recognition performance between three algorithms for noise robustness

Algorithm	Figure 6(a) Success Rate	Figure 6(b) Success Rate
Proposed Algorithm	97.50%	95.83%
Algorithm from [?]	89.17%	85.00%
Algorithm from [?]	98.33%	96.67%

Table 3 data shows that compared with [?], both the proposed algorithm and [?] demonstrate superior robustness to noise interference. However, although [?] achieves higher recognition rates, Table 1 shows that convolutional neural network recognition algorithms require extensive training time.

6 Conclusion

This paper combines the high-dimensional mathematical tool of Stein-Weiss analytic functions with BP neural networks to directly extract edge features from color palmprint images. Pairwise geometric histogram feature vectors are constructed from the extracted palmprint edge features for palmprint recognition. Through experimental testing and comparative analysis, the proposed palmprint extraction and recognition algorithm not only extracts abundant and clear palmprint edge information but also ensures high recognition rates while maintaining fast operational speed, particularly demonstrating strong robustness to rotation and noise interference.

However, some noise points are visible in the extracted palmprint edge images. Therefore, future research directions will focus on further improving algorithm noise resistance while maintaining edge extraction precision and recognition efficiency.

References

[1] Zhang Peng. Palmprint recognition based on feature extraction [D]. Beijing: Beijing Institute of Technology, 2016.

[2] Zhao Dandan. Palmprint recognition based on deep learning [D]. Hohhot: Inner Mongolia Agricultural University, 2016.

[3] Kang Bing, Liu Fu, Wei Qiwei. Palmprint fine line feature extraction based on spectral fusion [J]. Journal of Jilin University: Engineering and Technology Edition, 2015, 45(4): 1274-1280.

[4] Li Mengwen. Palmprint recognition based on local joint edge and orientation patterns [D]. Hefei: Anhui University, 2018.

[5] Kang Wenxiong. Palm vein verification using multiple features and locality preserving projections [J]. The Scientific World Journal, 2014, 9(11): 1024-1028.

[6] Mei Zhili, Tao Haijun, Wang Jiaqiang. Study of Gabor filters on palmprint feature extraction [J]. Journal of China University of Metrology, 2015, 26(3): 347-352.

[7] Aykut M, Ekinci M. Developing a contactless palmprint authentication system by introducing a novel ROI extraction method [J]. Image & Vision Computing, 2015, 40(8): 65-74.

[8] Wu Jie, Ren Jiangtao. Two level palmprint recognition algorithm based on subspace features [J]. Computer Engineering and Applications, 2015, 51(11): 175-178.

[9] Shen Shasha. A novel palmprint recognition algorithm based on Curvelet invariant features of the surface [J]. Journal of East China Normal University: Natural Science, 2015(3): 98-104.

[10] Xing Rui. Research of image feature extraction algorithm in the application of palmprint recognition [D]. Changchun: Jilin University, 2017.

[11] Wang Lianjia. Palmprint recognition based on principle analysis charact and local binary pattern [J]. Computer Simulation, 2010, 27(11): 254-257.

[12] Xu Chengai, Liu Wei, Xiao hong. An adaptive genetic algorithm based on weighted hamming distance [J]. Journal of South China Normal University: Natural Science Edition, 2015, 47(6): 121-127.

[13] Li Liying, Su Bianping, Zhang Yan-bo, et al. Interval triangular fuzzy multiple-attribute decision making method based on hamming distance [J]. Mathematics in Practice and Theory, 2016, 46(17): 106-111.

[14] Chen Zhi, Huang Linlin. Palmprint recognition based on ICA an BP neural network [J]. Journal of Beijing University of Aeronautics and Astronautics, 2008(3): 290-294.

[15] Qi Shuang. Application of BP neural network in palmprint recognition [J]. Information & Communications, 2016(10): 24-25.

[16] Li Minghao. The research on palmprint recognition using gabor wavelet and support vector machine [J]. Hohhot: Inner Mongolia Agricultural University, 2011.

[17] Li Kunlun, Zhang Yaxin, Liu Lili, et al. Palmprint recognition based on improved PCA and SVM [J]. Computer Science, 2015, 42(S2): 146-150.

[18] Cui Jianming, Liu Jianming, Liao Zhouyu. Research of text categorization based on support vector machine [J]. Computer Simulation, 2013, 30(2): 299-302, 368.

[19] Wu Yongbin, Li Xingmin. Palmprint extraction method based on clifford algebra vector product [J]. Computer and Modernization, 2012(5): 45-47, 54.

[20] Huang Guoheng, Li Xingmin. Color palmprint feature extraction and recognition algorithm based on octonion [J]. Computer Engineering, 2012, 38(22): 28-33.

[21] Li Xingmin. The octonion analysis [D]. Beijing: Beijing University, 1998.

[22] Wu Mingzhu, Wang Xiaochan, Li Xingmin. New 3D vessel segmentation algorithm using the stein-weiss analytic function properties [J]. Journal of Image and Graphics, 2016, 21(4): 434-441.

[23] Ma Yang. The application of octonion and BP neural network in liver vessel segmentation [D]. Guangzhou: South China Normal University, 2014.

[24] Li Chunlei, Li Xiang. Analysis of GPS height fitting town control survey [J]. Geomatics & Spatial Information Technology, 2012(8): 173-174.

[25] Liu Endong. Pipeline defect recognition based on BP neural network [J]. Electronic Technology & Software Engineering, 2017(2): 11-12.

[26] Wu Mingzhu. Improvement of contour-based image retrieval using pairwise geometric histogram [D]. Guangzhou: Jinan University, 2006.

[27] Wang Zuowei. Palmprint recognition based on convolutional neural network [D]. Qingdao: Qingdao University of Technology, 2017.

Note: Figure translations are in progress. See original paper for figures.