LETTER

Gender Attribute Mining with Hand-Dorsa Vein Image Based on Unsupervised Sparse Feature Learning

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SUMMARY Gender classification with hand-dorsa vein information, a new soft biometric trait, is solved with the proposed unsupervised sparse feature learning model, state-of-the-art accuracy demonstrates the effectiveness of the proposed model. Besides, we also argue that the proposed data reconstruction model is also applicable to age estimation when comprehensive database differing in age is accessible.
key words: *gender recognition, unsupervised sparse feature learning, data reconstruction*

1. Introduction

Vein recognition, as an emerging and prosperous branch of biometric identification, has attracted numerous research attentions due to its outperformed characteristics of being unique, permanent and live recognition [1]. However, to the best of our knowledge, there have been no publications aiming at gender classification with analysis on vein information. Instead, nearly all the related research focuses on vein feature extraction methods design, which serves as the key link for vein recognition task. Among all the reported feature extraction models, we intend to summarize them into four groups [2]: global topological analysis (GTA), global quantification analysis (GQA), local geometric analysis (LGA) and local invariant feature (LIF). Driven by the fact that the subject-specified hand-vein information could be well represented by the four models, is that possible to obtain effective gender-specified representation so that accurate gender classification result would be generated with similar methods? Four representative methods involving mean curvature [3], (2D)2PCA [4], LBP [5], SIFT [6], which corresponds to the four identity recognition groups, are made attempt with the lab-made database to figure out answer to our puzzle, extremely low classification accuracy as shown in Table 1, unlike the reported high EER in terms of vein recognition, is obtained, which indicates the poor ability of hand-crafted feature extraction model to solve problem of gender classification utilizing the hand-dorsa vein information.

Driven by the fact that learned feature obtained by unsupervised feature learning model have matched or outperformed numerous hand-crafted feature in both image classification and recognition task [7], [8], an unsupervised sparse feature learning model (USFL) to learn the statistical representation of specific vein information only differing in gender is proposed in this letter. The new feature learning model is easy to implement and free of complicated hyperparameter tuning (only the number of features to learn is tunable) when compared with the restricted Boltzmann machines (RBM) [9], denoising autoencoders [10] and sparse coding [11]. The USFL model works by making the learned feature distribution sparse and linear separable (as shown in Fig. 1), and the core design to give rise to the simple formulation and efficient learning with large input is not to explicitly modeling the original distribution but to optimize a simple cost function to make the feature distribution population sparsity, lifetime sparsity and high dispersal [12]. What's more, the establishment of the simple but effective USFL model is intuitively motivated by the fact that gender classification with vein information is a new problem to be investigated, and models with various tunable hyperparameters, which are unable to ensure positive experimental results, is usually unreasonable and not preferable.

Table 1 Gender classification result with four representative vein recognition algorithms.

Category	GTA	GQA	LGA	LIF
Methods	Mean Curvature	(2D)2PCA	LBP	SIFT
Accuracy(%)	0.325	0.573	0.257	0.192

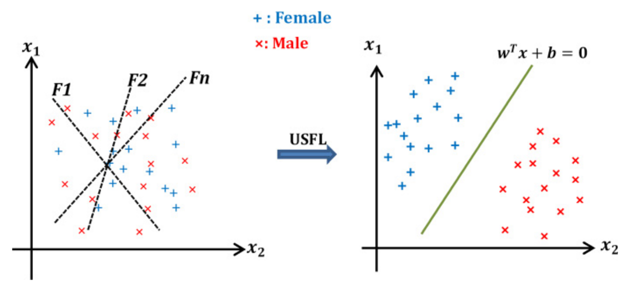

Fig. 1 Effect of the USFL model (F1∼Fn represents the false boundary)

2. Unsupervised Sparse Feature Learning (USFL)

The specific sparse feature learning model is realized by training a two-layered network with greedy layer-wise strategy. During the training process of each layer, the same pro-

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Table 2 Algorithm of USFL model

Unsupervised sparse feature learning
1. Input: N examples of hand vein images
2. Pre-processing: Data normalization by "bsxfun(@minus, data, mean(data))"
3. Original feature matrix generation:
$f_j^i = \sqrt{\epsilon + \left(w_j^T X^i\right)^2}$ where X^i is the input image matrix and f_j^i is the feature matrix for later process
4. Two-layered network training with layer-wised strategy:
4.1 First layer training
Input: Original feature matrix
ℓ_2-normalization: First $\widetilde{f}_j = f_j / \|f_j\|_2$ by rows;
then $\widehat{f}^i = \widetilde{f}^i / \|\widetilde{f}^i\|_2$ by columns
Objective construction with ℓ_1 penalty:
minimize $\sum_{i=1}^N \|\widehat{f}^i\|_1 = \sum_{i=1}^N \left\| \frac{\widetilde{f}^i}{\|\widetilde{f}^i\|_2} \right\|_1$
Objective optimization:
Using L-BFGS package to minimize objective
Until convergence
4.2 Second layer training
Input: Feature matrix optimized by first layer training
Training: The same procedure with 4.1
Output: Sparse feature matrix

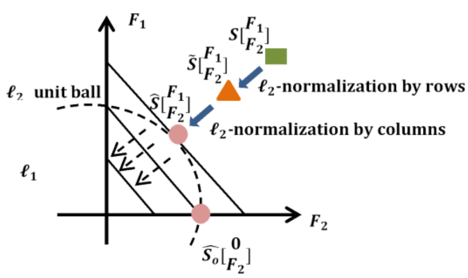


Fig. 2 Transformation illustration resulted by ℓ_2-normalization and minimizing objective with ℓ_1 penalty

cedure involving minimize the constructed objective function with ℓ_1 penalty based on ℓ_2-normalization is followed, and the L-BFGS package is adopted to optimize the objective function until convergence. The specific procedure of USFL model is illustrated as Table 2, note that f_j^i represents the value of j^{th} feature (row) corresponding to the i^{th} example (column).

The key to obtain the feature matrix with sparse distribution is by importing idea of ℓ_2-normalization and ℓ_1 penalty rule to construct objective followed by minimizing the objective, and we will prove how the design would result in sparse distribution as illustrated in Fig. 2.

It is known from Table 2 and Fig. 2 that $\hat{S}\begin{bmatrix}F_1\\F_2\end{bmatrix}$ would be generated from $S\begin{bmatrix}F_1\\F_2\end{bmatrix}$ when conducting ℓ_2-normalization from rows to columns respectively and thus $\hat{S}\begin{bmatrix}F_1\\F_2\end{bmatrix}$ is projected onto the ℓ_2 unit ball as shown in Fig. 2. Subsequently, the ℓ_2-normalized feature distribution would be further processed for sparseness with ℓ_1 penalty. Based on the spatial relationship of ℓ_1-norm and ℓ_2-norm, a simple but possible feature matrix transformation resulted by minimizing the objective is as the $\widehat{S_O}\begin{bmatrix}0\\F_2\end{bmatrix}$ from $\hat{S}\begin{bmatrix}F_1\\F_2\end{bmatrix}$, where the answered feature matrix is sparse with some value of feature matrix is zero, and this transformation would ensure the population sparsity of resulted feature matrix. What's more, it is also proved in [14] that both the lifetime sparsity and high dispersal are obtained with the proposed learning method.

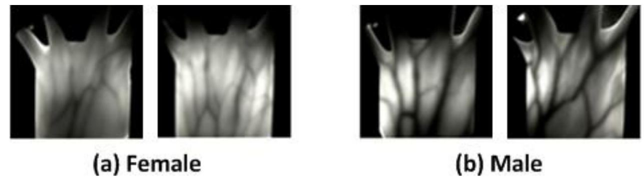


Fig. 3 Samples of Lab-made database

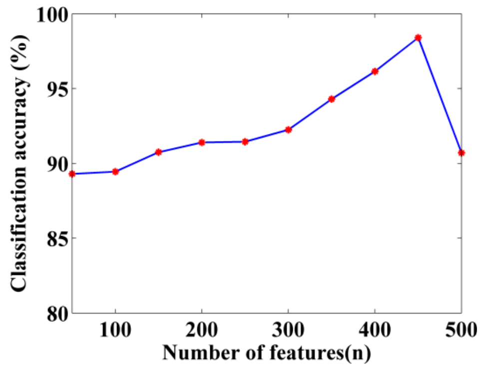
3. Lab-Made Hand-Dorsa Vein Database with Gender Information Annotated

To obtain persuasive and satisfactory classification result, a comprehensive hand-dorsa vein database with gender as samples' label is built containing 98 females and 102 males whose ages vary from 19 to 62. For each sample, 10 hand-dorsal vein images were acquired in two specifically set sessions separated by a time interval of more than 10 days, and at each time, five images were acquired from each subject at the wavelength of 850 nm, Fig. 3 shows some samples of male and female in the dataset. To the fullest of the dorsal vein information, we set the size of the images as $460 * 680$ with extremely high-quality. The ROI extraction [14] process specifically designed for this database is conducted followed by the grey and size normalization.

4. Experiments and Analysis

To rigorously evaluate the classification ability of the USFL model, the lab-made comprehensive vein examples are sent into the two-layered model as illustrated in Table 2. It should be noted that the ROI of the image is firstly extracted and then normalized as $100 * 100$ resulting in the $100 * 10000$ original vein image matrix followed by being sent into the training model, the linear SVM is adopted in the classification part. As for the parameters set, only ϵ of original matrix generation function and the number of features n are tunable, where ϵ is set as 10^{-8} resulting $f_j^i = \sqrt{\epsilon + \left(w_j^T X^i\right)^2} \approx \left|w_j^T X^i\right|$. Taking the time consumption, proportional to the number of features, and convergence control into account, the maximum number of features is set as 500. The specific classification accuracy with different set of n and corresponding time consumption is as shown in Fig. 4.

It can be clearly concluded from Fig. 4 (a) that relatively satisfied result is obtained with the two-layered USFL



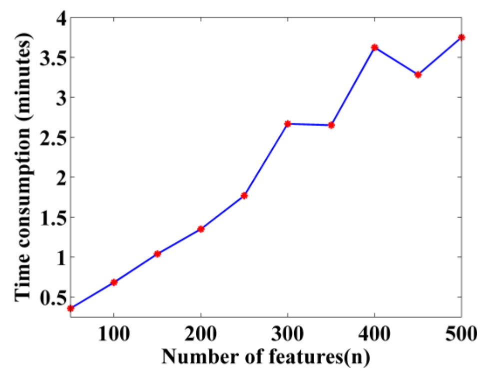


Fig. 4 Illustration of the experimental results. (a) Trend of classification accuracy with number of features change. (b) Total time consumption with number of features change

model, where the highest accuracy is 98.2% (n = 450) and the lowest one is 89.2% (n = 50). Besides, we regard the phenomenon including decrease from "n = 450" to "n = 500" and non-monotonic changing trend with classification accuracy as a result of noise information influence. However, the high time consumption (as shown in Fig. 4 (b)) whatever the number of features is needed to be further improved, and even the lowest one has cost a total of 0.716 minutes (42.96 s) until two-layered model training are finished.

5. Conclusions

This letter investigates a completely new research field of gender classification based on hand vein information, and a two-layered USFL model belonging to unsupervised learning is proposed to solve the problem. The core idea of the model is not to extract specific feature but to transform the original feature matrix generated by soft-absolute function into sparse distribution one so that a linear SVM model is able to figure out good classification result. The realization of sparseness within each layer on the feature matrix is by combining ℓ_2-normalization from rows to columns and ℓ_1 penalty to construct objective, and then matrix optimization by minimizing the objective is solved to obtain the linear-separable and sparse matrix. The solution to objective optimization is achieved by L-BFGS and model training of each layer is achieved by canonical greedy layerwise approach. The obtained state-of-the-art classification result as high as 98.2% fully demonstrates the effectiveness of the proposed USFL model.

Besides, it is convinced that the proposed simple unsupervised learning algorithm with only one parameter to tune is appropriate for other pattern recognition task. Thus a further vein recognition system based on USFL model would be implemented in future work, and also we tend to develop a novel vein recognition system where different feature extraction and classification methods are designed in terms of male or female for better identification result, and then the gender classification model is incorporated as a pre-processing step in our future vein recognition system.

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