SIFT FLOW BASED GENETIC FISHER VECTOR FEATURE FOR KINSHIP VERIFICATION

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ABSTRACT

Anthropology studies show that genetic features are inherited by children from their parents resulting in visual resemblance between them. This paper presents a novel SIFT flow based genetic Fisher vector feature (SF-GFVF) which enhances the facial genetic features for kinship verification. The proposed SF-GFVF feature is derived by applying a novel similarity enhancement method based on SIFT flow and learning an inheritable transformation on the Fisher vector feature so as to enhance and encode the genetic features of parent and child image in kinship relations. In particular, the similarity enhancement method is first presented by applying the SIFT flow algorithm to the densely sampled SIFT features in order to intensify the genetic features. Further analysis shows the relation of the extracted genetic features to anthropological results and discovers interesting patterns in different kinship relations. Finally, an inheritable transformation is applied to the enhanced Fisher vector feature which is learned with the criterion of minimizing the distance between kinship samples and maximizing the distance between non-kinship samples. Experimental results on the two representative kinship databases, namely the KinFace W-I and the Kinship W-II data sets show that the proposed method is able to outperform other popular methods.

***Index Terms*—** SIFT flow based genetic Fisher vector feature, kinship verification, inheritable transformation.

1. INTRODUCTION

Kinship verification from facial images, which is an emerging research area in computer vision, has gained increasing attention in recent years [1], [2], [3], [4], [5]. Pioneer works in anthropology [6], [7] believe that there are some genetic related features which are inherited by children from its parents that can be used to determine the kinship relations.

Kinship verification is a challenging task as the correlated visual resemblance between parents and their offspring have to be captured. In order to effectively classify kinship relations, the genetic features between parent and child have to be enhanced and encoded in the feature representation. Many feature representation methods such as LBP [8], Gabor features [9], Fisher vector [10], learning-based (LE) descriptor [11], etc. have been proposed for representing face images. But these methods are not explicitly designed in order to capture and enhance the similarities and genetic relations between parent and child images. Another issue is that unlike traditional face recognition problem, the similarity gap between kinship images is much larger specifying the need for more powerful visual features.

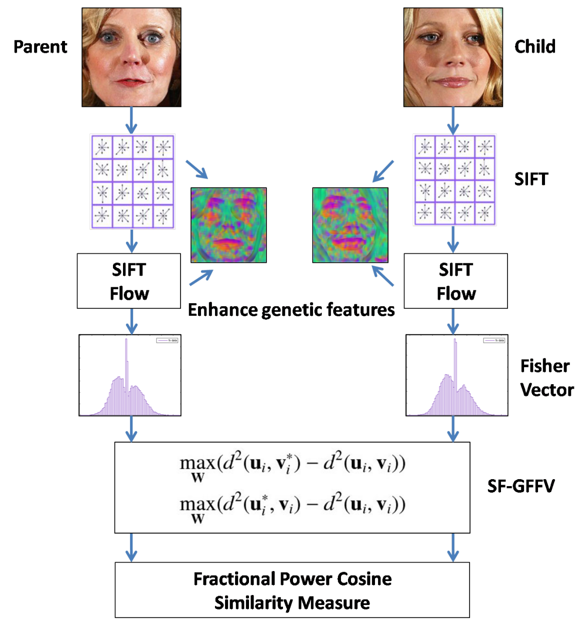

Fig. 1. The framework of our proposed SF-GFVF feature.

To address these issues, this paper proposes a novel SIFT flow based genetic Fisher vector feature with applications to kinship verification. We enhance the genetic inheritable features of parent and child image in kinship relations by matching densely sampled SIFT features and visual correspondence between them using the SIFT flow algorithm [15]. We analyze and correlate the enhanced genetic features to the anthropological results and find interesting patterns in different kinship relations. We then apply an inheritable transformation with the objective of pushing the non-kinship samples as far as possible and pulling the kinship samples as close as possible. The experimental results on the two challenging kinship databases, the KinFace W-I and the Kinship W-II dataset [3] show the effectiveness of the proposed method. The framework of our proposed method is illustrated in figure 1.

2. RELATED WORK

Several research efforts have been invested in kinship verification by the anthropology and the computer vision community. Studies [6, 7] in anthropology have confirmed that children resemble their parent more than other people and they may resemble a particular parent more at different ages. Lu et al. [3] proposed neighborhood repulsed metric learning (NRML) in which the intraclass samples within a kinship relation are pulled as close as possible and interclass samples are pushed away for kinship verification. Dehghan et al. [4] proposed to apply the generative and the discriminative gated autoencoders to learn the genetic features and metrics together for kinship verification. Lu et al. [12] presented the results of various teams on the FG 2015 Kinship Verification in the Wild challenge.

Many feature representation methods have been proposed to represent face images. Liu et al. [9] showed the effectiveness of Gabor features for face recognition. Wolf et al. [13] proposed the three-patch LBP computed by comparing the values of three patches. Cao et al. [11] proposed the learning-based (LE) descriptor which is learned by unsupervised learning techniques. Simonyan et al. [10] proposed to apply the Fisher vectors [14] for face verification which achieves very good performance.

3. SIFT FLOW BASED GENETIC FISHER VECTOR FEATURE

3.1. SIFT Flow based Similarity Enhancement Method

We present a novel similarity enhancement method by extending the SIFT flow algorithm [15] for kinship images so as to find inheritable feature relations between the kinship images and enhance the similarities between them. The SIFT flow algorithm matches the densely sampled SIFT features and finds the correspondence estimated by SIFT flow. It can be formulated similarly as the optical flow wherein SIFT descriptors are matched instead of the pixel to pixel correspondences between two images. The SIFT flow is based on the criteria that the SIFT descriptors are matched along the flow vectors and the flow field is smooth [15]. The energy function for SIFT flow [15] is defined as follows:

$$\begin{aligned} E(\mathbf{w}) = \sum_{\mathbf{p}} \min(\|s_1(\mathbf{p}) + s_2(\mathbf{p}+\mathbf{w}(\mathbf{p}))\|_1, t) + \\ \sum_{\mathbf{p}} \eta(|u(\mathbf{p}) + v(\mathbf{p})|) + \sum_{\mathbf{p},\mathbf{q}\epsilon\varepsilon} \min(\alpha|u(\mathbf{p}) + u(\mathbf{q})|, d) + \\ \min(\alpha|v(\mathbf{p}) + v(\mathbf{q})|, d) \end{aligned} \tag{1}$$

where $\mathbf{p} = (x, y)$ are the grid coordinate of images, $\mathbf{w}(\mathbf{p}) = (u(\mathbf{p}), v(\mathbf{p}))$ is the flow vector at $\mathbf{p}$, s_1, s_2 are the two SIFT images to be matched and ε contains all the spatial neighborhoods.

To visualize the SIFT images, the top three principal components of the SIFT image are mapped to the principal components of the RGB space, as shown in figure 2. The purple and the orange regions in the visualization highlight the inheritable genetic feature regions in the kinship images. Our objective is to enhance these genetic regions in the kinship images. For a query parent-child image pair, the SIFT flow is applied to match dense correspondences between the parent and the child SIFT descriptors. If the image pair is in kinship relation, the genetic facial regions are enhanced by adding weights to those specific facial regions.

Our proposed similarity enhancement method results in interesting phenomena that correlate the enhanced genetic features to the anthropological features. Naini et.al [16] analyzed the contributions of heredity and environment on external facial features. The relative strength of genetic influence on different facial parameters is assessed using optical surface scanning and twin method. The anthropological results [16] show that eyes, chin and parts of the forehead show higher visual resemblance between parent and their offspring and provide large feedback. The results shown in figure 2 show high correlation to the anthropological results with high feedback in parts of forehead and eye regions. Interesting patterns can be deduced for different relations from figure 2. It can be observed that the father-son and mother-daughter relation show large visual correspondence in different parts of facial regions leading to the deduction that individuals of the same gender in kinship relations share higher visual resemblance. It can also be seen that mother-daughter relation has higher genetic responses compared to father-daughter relation confirming the observation that mothers resemble their daughters more as in [6].

3.2. Inheritable Genetic Transformation

We first briefly review the Fisher vector method. Fisher vector is widely used for visual recognition problems such as face recognition [10], object recognition [14]. Particularly, let $\mathbf{X} = \{\mathbf{d}_t, t = 1, 2, ..., T\}$ be the set of T local descriptors extracted from the image. Let μ_λ be the probability density function of $\mathbf{X}$ with a set of parameters λ, then the Fisher kernel [14] is defined as follows: $K(\mathbf{X}, \mathbf{Y}) = (\mathbf{G}_\lambda^X)^T \mathbf{F}_\lambda^{-1} \mathbf{G}_\lambda^Y$ where $\mathbf{G}_\lambda^X = \frac{1}{T} \bigtriangledown_\lambda \log[\mu_\lambda(\mathbf{X})]$, which is the gradient vector of the log-likelihood that describes the contribution of the parameters to the generation process. And $\mathbf{F}_\lambda$ is the Fisher information matrix of μ_λ. Essentially, the Fisher vector is derived from the explicit decomposition of the Fisher kernel as the symmetric and positive definite Fisher information matrix $\mathbf{F}_{\boldsymbol{\lambda}}$ has a Cholesky decomposition as $\mathbf{F}_{\boldsymbol{\lambda}}^{-1} = \mathbf{L}_{\boldsymbol{\lambda}}^T \mathbf{L}_{\boldsymbol{\lambda}}$. Therefore, the Fisher kernel $K(\mathbf{X}, \mathbf{Y})$ can be written as a dot product between two vectors $\mathbf{L}_{\boldsymbol{\lambda}} \mathbf{G}_{\boldsymbol{\lambda}}^{\mathbf{X}}$ and $\mathbf{L}_{\boldsymbol{\lambda}} \mathbf{G}_{\boldsymbol{\lambda}}^{\mathbf{Y}}$ which are defined as the **Fisher vectors** of **X** and **Y** respectively. Fisher vector

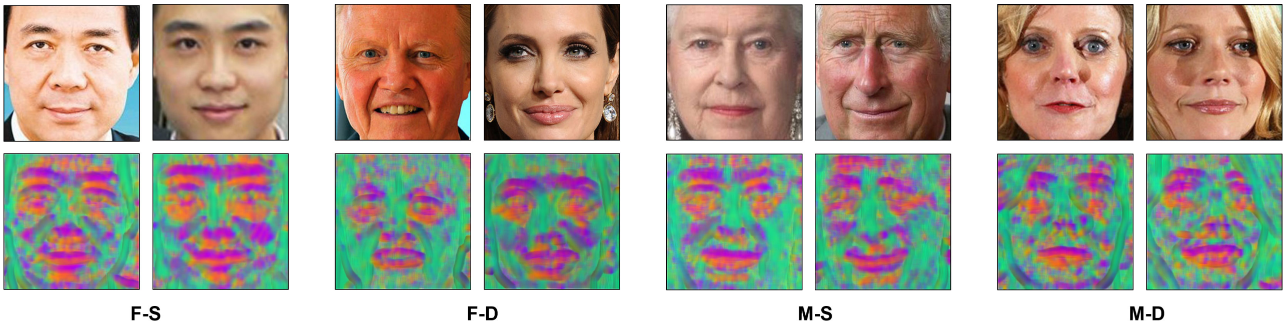

Fig. 2. Visualization of SIFT images of different kinship relations using the top three principal components of SIFT descriptors. The purple and orange regions in the visualization highlight the inheritable genetic feature regions in the kinship images.

focuses on the image specific features and discards the image independent features but this does not guarantee enhancement of genetic features in parent and child images.

We therefore learn an inheritable genetic transformation $\mathbf{W}$ on the SIFT flow based genetic Fisher vector $\mathbf{p}_i(i = 1, 2, ..., m)$ and $\mathbf{c}_i(i = 1, 2, ..., m)$ for each training pairs ($\mathbf{p}_i$, $\mathbf{c}_i$) where $\mathbf{p}_i$ denotes the parent image and $\mathbf{c}_i$ denotes the child image. The learned SF-GFVF for the parent and child image are as follows: $\mathbf{u}_i = \mathbf{W}^T\mathbf{p}_i$ and $\mathbf{v}_i = \mathbf{W}^T\mathbf{c}_i$. The objective of learning the inheritable transformation is to minimize the distance between $\mathbf{u}_i$ and $\mathbf{v}_i$ if $\mathbf{u}_i$ and $\mathbf{v}_i$ have kinship relations and maximize the distance otherwise.

Let $\mathbf{D} = \{(\mathbf{u}_i, \mathbf{v}_i)|\mathbf{u}_i, \mathbf{v}_i \in \mathbb{R}^{n\times1}(i = 1, 2, ..., m)\}$ be the training data that consists of m pairs of SIFT flow based genetic Fisher vector features derived from the kinship images. Therefore, multiple objectives for the SF-GFVF method can be formulated as:

$$\begin{aligned} &\max_{\mathbf{W}}(d^2(\mathbf{u}_i, \mathbf{v}_i^*) - d^2(\mathbf{u}_i, \mathbf{v}_i)) \\ &\max_{\mathbf{W}}(d^2(\mathbf{u}_i^*, \mathbf{v}_i) - d^2(\mathbf{u}_i, \mathbf{v}_i)) \end{aligned} \tag{2}$$

where $d^2(\mathbf{u}_i, \mathbf{v}_i) = (\mathbf{p}_i - \mathbf{c}_i)^T\mathbf{W}\mathbf{W}^T(\mathbf{p}_i - \mathbf{c}_i)$, $\mathbf{u}_i^*$ is the nearest neighbor of $\mathbf{u}_i$ and $\mathbf{v}_i^*$ is the nearest neighbor of $\mathbf{v}_i$. Note that there are 2*m objective functions in equation 2 since $i = 1, 2, ..., m$.

In practice, it is difficult to solve a multiple objective problem for high dimensions since it is computationally expensive and a single solution may not exist. Therefore, linear scalarization [17] is applied in order to convert the multi-objective problem into a single objective function with a weighted sum of the individual objective functions. Assuming the same weight λ_i^2 for the objective functions of each training pair $(\mathbf{u}_i, \mathbf{v}_i)$, we want to maximize the following objective function:

$$\begin{aligned} &\max_{\mathbf{W}} \sum_{i=1}^{m} \lambda_i^2 (d^2(\mathbf{u}_i, \mathbf{v}_i^*) + d^2(\mathbf{u}_i^*, \mathbf{v}_i) - 2 * d^2(\mathbf{u}_i, \mathbf{v}_i)) \\ &s.t. \sum_{i=1}^{m} \lambda_i = 1, \mathbf{W}^T\mathbf{W} = \mathbf{I} \end{aligned} \tag{3}$$

Then objective function in equation 3 can be further simplified as Tr $(\mathbf{W}^T(\mathbf{Q}_1 + \mathbf{Q}_2 - 2\mathbf{Q}_3)\mathbf{W})$ where $\mathbf{Q}_1 = \sum_{i=1}^{m} \lambda_i^2(\mathbf{p}_i - \mathbf{c}_i^*)(\mathbf{p}_i - \mathbf{c}_i^*)^T$. $\mathbf{Q}_2$ and $\mathbf{Q}_3$ can be computed in a similar way.

Then the algorithm of optimizing the objective function in equation 3 is summarized as follows.

Algorithm 1 SF-GFVF Learning Algorithm

Input: Training Images: $\mathbf{D} = \{(\mathbf{u}_i, \mathbf{v}_i)|\mathbf{u}_i, \mathbf{v}_i \in \mathbb{R}^{n\times1}(i = 1, 2, ..., m)\}$

Output: Inheritable tranformation $\mathbf{W}$

1: **Step 1 (Initialization)**
Initialize $\lambda_i = 1/m$ and $\mathbf{W} = \mathbf{I}$

2: **Step 2 W is fixed, optimize on λ_i**

$$\lambda_i = \frac{f^{-1}(\mathbf{u}_i, \mathbf{v}_i)}{\sum_{i=1}^{m} f^{-1}(\mathbf{u}_i, \mathbf{v}_i)} \tag{4}$$

where $f(\mathbf{u}_i, \mathbf{v}_i) = d^2(\mathbf{u}_i, \mathbf{v}_i^*) + d^2(\mathbf{u}_i^*, \mathbf{v}_i) - 2 * d^2(\mathbf{u}_i, \mathbf{v}_i)$

3: **Step 3 λ_i is fixed, update W**

$$\begin{aligned} &\max_{\mathbf{W}} \mathrm{Tr}(\mathbf{W}^T(\mathbf{Q}_1 + \mathbf{Q}_2 - 2\mathbf{Q}_3)\mathbf{W}) \\ &s.t. \mathbf{W}^T\mathbf{W} = \mathbf{I} \end{aligned} \tag{5}$$

4: **Step 4 Continue to Step 2 if not converged**

After the SF-GFVF is derived, principal component analysis with whitening transformation is applied in order to extract the most expressive features. A fractional power cosine similarity measure (FPCSM) is then applied as follows to compute the similarity between two images.

$$FPCSM(\mathbf{u}_i, \mathbf{v}_i) = CS(sign(\mathbf{u}_i)|\mathbf{u}_i|^{\alpha}, sign(\mathbf{v}_i)|\mathbf{v}_i|^{\alpha}) \tag{6}$$

where $CS(\mathbf{a}, \mathbf{b}) = \frac{\mathbf{a}^T\mathbf{b}}{||\mathbf{a}||||\mathbf{b}||}$ is the traditional cosine similarity measure and α $(0 < \alpha < 1)$ is the power parameter.

The linear scalarization optimization procedure may be similar to metric learning methods such as NRML [3] in terms of mathematical formulas but the differences are as follows. (i) Our method uses multiple objective function instead of a common global objective function which helps to prevent dominance of one term in the function over other terms. (ii) Our method enhances the genetic features in kinship images and is proposed from the feature learning point of view and not the metric learning point of view.

4. EXPERIMENTS

This section demonstrates the performance of our proposed method on two challenging kinship databases: the KinFaceW-I dataset and the KinFaceW-II dataset [3]. There are four kinship relations in both the datasets: father-son (F-S), father-daughter (F-D), mother-son (M-S), and mother-daughter (M-D). In KinFaceW-I dataset, each image pair in the kinship relation was acquired from different photos whereas in KinfaceW-II, they were obtained from the same photo. In the KinFaceW-I dataset, there are 156, 134, 116, and 127 image pairs for each of the relations defined above. In the KinFaceW-II dataset, there are 250 pairs of the images for each relation. In our experiments, we conduct 5-fold cross validation where both datasets are divided into five folds having the same number of image pairs [3].

4.1. Comparison with other popular methods

This section presents the comparison between our proposed SF-GFVF method and other state-of-the-art deep learning and metric learning methods. In table 1 and 2, ANTH denotes anthropological results, GGA denotes gated autoencoders and DGA denotes discriminative autoencoders. It can be observed that the result on the KinFace W-II dataset is better than the KinFace W-I dataset due to the availability of more training samples. Another reason is that the KinFace W-II dataset contains kinship images from the same photo therefore helps to reduce the illumination and background noise compared to the KinFace W-I dataset which contains kinship images from the different photos. Experimental results in table 1 and table 2 show that our method outperforms deep learning methods [4] and other metric learning based methods.

Methods	F-S	F-D	M-S	M-D	Mean
CSML [18]	61.10	58.10	60.90	70.00	62.50
NCA [19]	62.10	57.10	61.90	69.00	62.30
LMNN [20]	63.10	58.10	62.90	70.00	63.30
NRML [3]	64.10	59.10	63.90	71.00	64.30
MNRML [3]	72.50	66.50	66.20	72.00	69.90
ITML [21]	75.30	64.30	69.30	76.00	71.20
GGA [4]	70.50	70.00	67.20	74.30	70.50
ANTH [4]	72.50	71.50	70.80	75.60	72.60
DGA [4]	76.40	72.50	71.90	77.30	74.50
SF-GFVF	76.27	**74.64**	**75.48**	**79.98**	**76.09**

Table 1. Comparison between the SF-GFVF and other popular methods on the KinFaceW-I dataset

Methods	F-S	F-D	M-S	M-D	Mean
CSML [18]	71.80	68.10	73.80	74.00	71.90
NCA [19]	73.80	70.10	74.80	75.00	73.50
LMNN [20]	74.80	71.10	75.80	76.00	74.50
NRML [3]	76.80	73.10	76.80	77.00	75.70
MNRML [3]	76.90	74.30	77.40	77.60	76.50
ITML [21]	69.10	67.00	65.60	68.30	67.50
GGA [4]	81.80	74.30	80.50	80.80	79.40
DGA [4]	83.90	76.70	83.40	84.80	82.20
SF-GFVF	**87.20**	**79.60**	**88.00**	**87.80**	**85.65**

Table 2. Comparison between the SF-GFVF and other popular methods on the KinFaceW-II dataset

KinFaceW-I	F-S	F-D	M-S	M-D	Mean
FV	75.02	70.56	65.49	78.39	72.37
SF-GFVF	**76.27**	**74.64**	**75.48**	**79.98**	**76.09**
KinFaceW-II	F-S	F-D	M-S	M-D	Mean
FV	80.00	68.60	79.40	78.20	76.55
SF-GFVF	**87.20**	**79.60**	**88.00**	**87.80**	**85.65**

Table 3. Comparison between the SF-GFVF and Fisher vector on the KinFaceW-I and KinFaceW-II dataset

4.2. Comparison Between SF-GFVF and FV

This section presents the comparison between our proposed SF-GFVF method and the original Fisher vector (FV) [14] method. Experimental results in table 3 show that our proposed SF-GFVF method improves upon the original FV method by approximately 4 percent and 9 percent in the KinFace W-I and KinFace W-II datasets respectively. The reason is that the original Fisher vector method focuses on image specific features but it does not enhance the genetic features in kinship images. Our method uses the SIFT flow algorithm and inheritable transformation to encode and enhance the facial genetic features in kinship relations.

5. CONCLUSION

This paper presents a SIFT flow based inheritable Fisher vector feature (SF-GFVF) for kinship verification. The proposed SF-GFVF feature uses SIFT flow algorithm to enhance the genetic features in kinship images. An inheritable transformation is then applied to the enhanced Fisher vector by optimizing multiple objective functions. Experimental results show that the proposed method is able to outperform other popular methods for kinship verification.

6. REFERENCES

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