2018 UKSim-AMSS 20th International Conference on Modelling & Simulation

Hu Li Moments for Low Resolution Thermal Face Recognition

Naser Zaeri
Faculty of Computer Studies
Arab Open University
P.O. Box 3322 Safat 13033, Kuwait
Email: n.zaeri@aou.edu.kw

Abstract — **In this paper, we present a new technique for low resolution face recognition using Hu Li moment invariants. The new technique can handle the issue of low resolution images very efficiently by the virtue of thermal face characteristics. The new technique will be tested on a new database comprising of images of different expressions, and were taken within different time-lapse. Experiments have resulted to almost consistent recognition rates. The proposed technique offers outstanding discriminability and performs efficiently, with an average recognition rate of ~94% over the various resolutions.**

Keywords* — *face recognition, low resolution, thermal image, moment invariants.

I. INTRODUCTION

Visible-spectrum images have high variability because they are produced by reflection in surfaces, which has strong dependence on luminosity and spatial distribution of the light sources which usually have strong differences in time. Light reflected from human faces also varies depending on the skin colour of people from different ethnic groups. This variability, coupled with dynamic lighting conditions, may cause great difficulties in recognizing the face in applications such as outdoor surveillance tasks [1].

Recently, researchers have investigated the use of thermal imagery for face recognition with good results. The advantage gained from working with the Infrared (IR) imagery type of sources is that the eye is not sensitive in this range, and illumination can be used in a more flexible way. The anatomical information imaged by infrared technology involves subsurface features believed to be unique to each person. Also, the IR face recognition, being not vulnerable to facial skin and expressions, can eliminate the drawbacks of face recognition in visible light.

Although a great deal of work has aimed at developing robust face recognition algorithms, relatively limited work has focused on adapting the technology to applications where the face image is characterized by its low resolution. Most of the current algorithms for face recognition do not consider images of low resolution that commonly exist in real life applications [2]. Apparently, high resolution images can be available in labs or in well-controlled environment. But when it comes to real situations, things become more complicated and turn out it need more practical handling.

In this paper, we present a new technique for low resolution face recognition using Hu Li moment invariants. Moments invariants offer robustness against variability due to the changes in regions of the objects. To the best of our knowledge, no work has discussed low resolution situation in thermal domain. The organization of the paper is as follows. A brief literature review is given in Section 2. Section 3 furnishes the mathematical background of the new method. The experimental results are discussed in Section 4. Finally, the paper is brought to a conclusion in Section 5.

II. LITERATURE REVIEW

Despite the great advances in the field of research, face-based identification still poses many challenges. In recent years, researchers started investigating the thermal imagery for face recognition. In thermal imagery of human tissue, the major blood vessels have weak sigmoid edges. This is due to the natural phenomenon of heat diffusion, which means that when two objects with different temperatures are in contact (e.g. vessel and surrounding tissue), heat conduction creates a smooth temperature gradient at the common boundary [3].

Authors in [4] proposed an approach using wide-baseline matching of face vascular networks obtained from thermal images. The vascular networks are obtained through skin segmentation and morphological operators. The image matching stage uses SIFT descriptors for verifying correspondences and generating a final geometrical transformation that relates the vascular networks. Furthermore, the general parameters for the Gaussians cannot be obtained, as they depend on the response of the particular camera to thermal intensity. The authors have reported a best recognition rate of 95.7% for a small database that consists of 156 thermal images.

A combination of principal component analysis technique and a Bayesian Maximum Likelihood for thermal face image classification was proposed in [5]. The Bayesian approach uses a probabilistic measure of similarity based on a Bayesian Maximum Likelihood analysis of image differences. In this work, the authors have developed nonlinear technique for multispectral face recognition. However, most of the obtained results were poor. Bayesian face recognition needs a sufficient number of face images for intrapersonal learning process and if the number of these

0-7695-6405-4/18/$31.00 ©2018 IEEE

DOI 10.1109/UKSim.2018.00026

images is low then the system performance will be inefficient.

Oz and Khan [6] found that variances in thermal intensity values recorded at facial thermal feature points can help classify intentional facial expression by using multivariate tests and linear discriminant analysis. Trujillo et al. [7] proposed localizing facial features in thermal images by detecting interest point and using clustering approach.

In [8], a co-transfer learning framework is proposed in which knowledge learnt in controlled high resolution environment is transferred for matching low resolution probe visible images with high resolution gallery. The proposed framework combines transfer learning and co-training to perform knowledge transfer by updating classifier's decision boundary with low resolution probe instances. The proposed co-transfer learning framework is applied on support vector machine (SVM) classifiers.

Wu et al. [9] presented convolutional neural network (CNN) architecture for thermal face recognition. CNN is a new type of neural network method which can automatically learn effective features from the raw data. Bi et al. [10] combined multiple features in thermal face characterization for face recognition. They designed a systematical way to combine four features, including Local binary pattern, Gabor jet descriptor, Weber local descriptor and Down-sampling feature. Experimental results show that their approach outperformed methods that leverage only a single feature and is robust to noise and occlusion.

Vigneau et al. [14] analyzed the problems produced by temporal variations of infrared face images when used in face recognition systems. The temporal variations present in thermal face images are mainly due to different environmental conditions, physiological changes of the subjects, and differences of the infrared detectors' responsivity at the time of the capture, which affect the performance of infrared face recognition systems. Authors created two thermal face databases that include capture sessions with real and variable conditions. They also proposed two criteria to quantify the temporal variations between data sets. The thermal face recognition systems have been developed using the following five methods: local binary pattern, Weber linear descriptor, Gabor jet descriptors, scale invariant feature transform, and speeded up robust features.

Liu and Yin [15] presented a new descriptor for spontaneous facial expression recognition from videos acquired by a thermal sensor. Thermal imaging can measure autonomic activities, which are the physiological changes evoked by the autonomic nervous system regardless of the variety and ambiguity of facial appearances. To get the local energy and temperature changes, authors proposed to use spatio-temporal orientation energy and acceleration of dense trajectory as low level features improve the discriminative capacity by aggregating the local feature using an improved fisher vector.

As we see from above brief discussion, the works tackling low resolution aspects of face images are mainly within the visible domain, not the thermal. The attempts to explore the potential of thermal face features in recognizing low resolution images are rare, if any. The next section shows how the new method can handle the issue of low resolution images very efficiently by the virtue of thermal face characteristics.

III. HU LI MOMENTS

The proposed method describes the thermal face images by a set of measurable quantities called invariants. These invariants are insensitive to changes that can convey enough discrimination to distinguish faces belonging to different classes. We represent each face by a *n*-dimensional vector space called feature space or invariant space.

Invariance to translation can be achieved by shifting the class such that its centroid coincides with the origin of the coordinate system. In this case, we have the central geometric moments

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^p (y-\bar{y})^q f(x,y) \tag{1}$$

where $f(x, y)$ is the image function and M, N are image dimensions, and $\bar{x} = m_{10}/m_{00}$, $\bar{y} = m_{01}/m_{00}$ are the coordinates of the class centroid.

It is important to choose the proper class of invariants with respect to expected image degradations and, eventually, take into consideration a method for the moment computation acceleration depending on the type and amount of data to be analysed [11]. Scaling invariance is obtained by proper normalization of each moment. Since low-order moments are more stable to noise and easier to calculate, researchers normalize most often by a proper power of μ_{00}

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\omega}} \tag{2}$$

$$\omega = \frac{p+q}{2} + 1 \tag{3}$$

where η_{pq} is called normalized central geometric moment.

In this regards, Hu invariants [12] attract the greatest attention for the object description and consecutive classification. Rotation moment invariants were first introduced by Hu, who employed the results of the theory of algebraic invariants and derived his seven famous invariants. The equations are given in (4–10) below. After Hu, various approaches to the theoretical derivation of moment invariants were published. Among those published works was Li [12] who used the Fourier-Mellin transform to derive invariants. He added five more equations to Hu equations, shown in (11–15) below. We describe every thermal face image with a feature vector consisting of these 12 invariants given in equations (4–15). In other word, for any feature vector say **a**, it is constructed in following way:

$\mathbf{a} = [\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6, \varphi_7, \varphi_8, \varphi_9, \varphi_{10}, \varphi_{11}, \varphi_{12}]$.
The Euclidean distance given in (16) is used as the system classifier, for vectors **a** and **b** both of *d* dimensions.

$$\varphi_1 = \eta_{20} + \eta_{02} \tag{4}$$

$$\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{5}$$

$$\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{6}$$

$$\varphi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{7}$$

$$\varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{8}$$

$$\varphi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \tag{9}$$

$$\varphi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{10}$$

$$\varphi_8 = \eta_{40} + \eta_{22} + \eta_{04} \tag{11}$$

$$\varphi_9 = (\eta_{40} - \eta_{04})^2 + 4(\eta_{31} - \eta_{13})^2 \tag{12}$$

$$\varphi_{10} = (\eta_{40} - 6\eta_{22} + \eta_{04})^2 + 16(\eta_{31} - \eta_{13})^2 \tag{13}$$

$$\varphi_{11} = (\eta_{40} - 6\eta_{22} + \eta_{04})^2[(\eta_{40} - \eta_{04})^2 + 4(\eta_{31} - \eta_{13})^2] + 16(\eta_{40} - \eta_{04}) + (\eta_{31} + \eta_{13})(\eta_{31} - \eta_{13}) \tag{14}$$

$$\varphi_{12} = (\eta_{40} - 6\eta_{22} + \eta_{04})^2[(\eta_{40} - \eta_{04})^2 + 4(\eta_{31} - \eta_{13})^2] - 16(\eta_{40} - \eta_{04}) + (\eta_{31} + \eta_{13})(\eta_{31} - \eta_{13}) \tag{15}$$

$$D(\mathbf{a}, \mathbf{b}) = \left(\sum_{k=1}^{d} (a_k - b_k)^2 \right)^{1/2} \tag{16}$$

IV. EXPERIMENTAL WORK

We have built a database consisting of 1500 frontal images for 20 different subjects taken in different sessions. We used the Infrared Camera ETIP 7320 which includes thermal infrared imaging radiometer using a micro-bolometer 320×240 focal plane array and a Vanadium Oxide technology base. Participants were asked to express three different emotions with their faces: neutral, anger, and smiling.

In order to test the system performance under practical situations, we have created four different space resolutions from the original 300 frontal images. More specifically, we evaluate the technique on images with four different resolutions of probe thermal images, beside the original high resolution images. The original high resolution images are of size 180×160. Images at a particular resolution are obtained by down-sampling the original images to the required resolution (namely, 90×80, 45×40, 22×20, and 18×16). We end up with 5 space resolutions × 300 images per resolution, giving a total of 1500 images. All subsets contain random images with eyeglasses. That is, we have images with eyeglasses at different resolutions (both in the training set and testing set). We refer to a 90×80 image as an image of 0.5 resolution, as the original (high) resolution image size 180×160 has been down-sampled by 50% (half) of its rows and columns. Similarly, the 45×40, 22×20, and 18×16 have been referred to as 0.25 (quarter), 0.125 (one-eighth), and 0.1 (one-tenth), respectively. Examples of images at various resolutions are shown in Figures 1–5.

The face image is first divided into components where the local characteristics and features are combined together using a certain fusion method. Each moment is trained on a determined cluster (component) of thermal images in the training database. Then, the local features are combined at a second stage to decide whether the input face image belongs to a given class. In our work, the image is divided into 16 equal-size and non-overlapped components. The results obtained from the similarity measures from the feature vectors for the different components are fused together using "voting" fusion to achieve the final similarity score. Fig. 6 shows an example of a 16-component thermal image at 0.25 resolution. The corresponding 3D temperature distribution for the 16 components is shown in Fig. 7. Fig. 8 shows the performance of the proposed technique. As the results reveal, the technique has shown impressive and stable performance with an average recognition rate of ~94%.

Fig. 1. An example of an original high resolution face image.

Fig. 2. An example of a face image of 0.5 resolution corresponding to the class of the image shown in Figure 1.

Fig. 3. An example of a face image of 0.25 resolution corresponding to the class of the image shown in Figure 1.

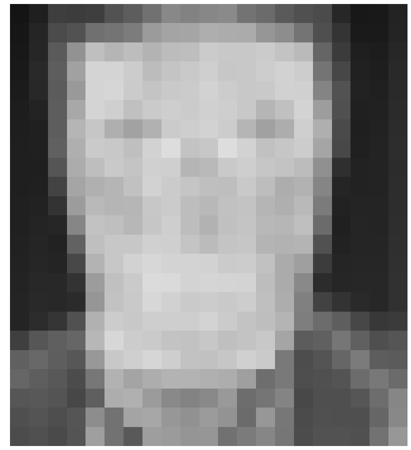

Fig. 4. An example of a face image of 0.125 resolution corresponding to the class of the image shown in Figure 1.

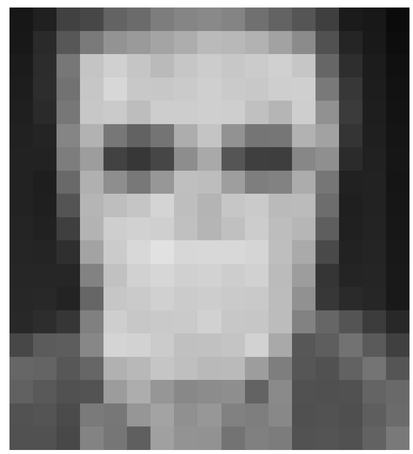

Fig. 5. An example of a face image of 0.1 resolution corresponding to the class of the image shown in Figure 1.

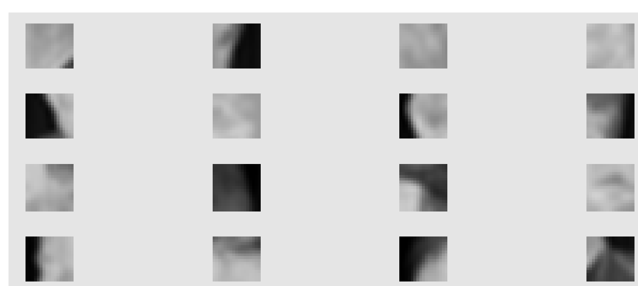

Fig. 6. An example of a 16-component thermal image at 0.25 resolution.

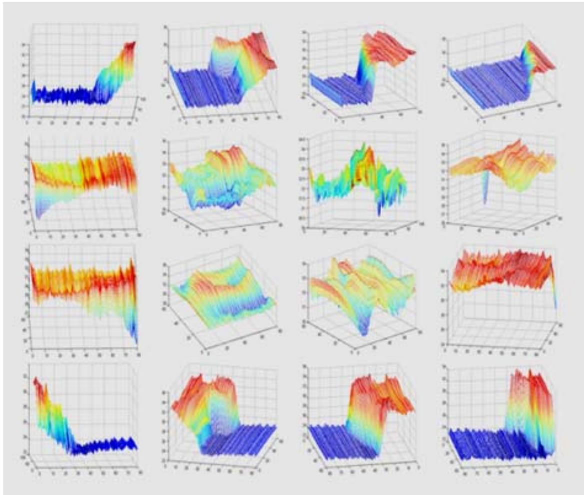

Fig. 7. An example of a 3D temperature distribution corresponding to Figure 6.

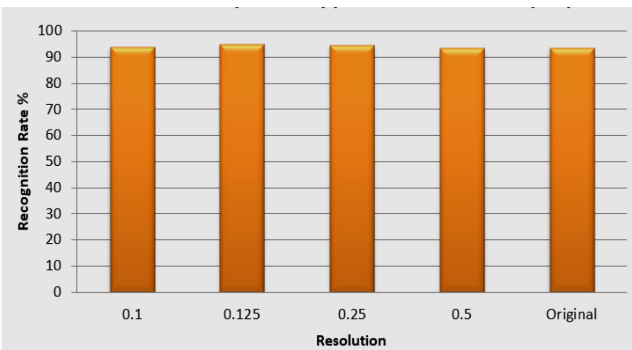

Fig. 8. Recognition rate vs. image resolution.

V. CONCLUSION

In this paper, we presented a new technique for low resolution face recognition using Hu Li moment invariants. The new technique can handle the issue of low resolution images efficiently by the virtue of thermal face characteristics. As the results reveal, the technique has shown impressive performance with an average recognition rate of ~94% at the various resolutions. Our future work will consider implementing the technique over images of different poses at various resolutions. Comparison with other moments invariants techniques will be considered as well.

REFERENCES

[1] B.A. Rajoub, R. Zwiggelaar, Thermal Facial Analysis for Deception Detection, IEEE Transactions on Information Forensics and Security, Volume: 9, Issue: 6, pp. 1015 – 1023, (2014).

[2] B. Liu and F. Wang, “Face Recognition Approach Based on 2D Discrete Fractional Fourier Transform”, IEEE 3rd International Conference on Communication Software and Networks, pp. 3155 – 3159, China, (2011).

[3] N. Zaeri, “Component-based Thermal Face Recognition,” British Journal of Applied Science & Technology, vol. 4, no. 6, pp. 945-966, (2014).

[4] Hermosilla G, Loncomilla P, Ruiz del Solar J. Thermal face recognition using local interest points and descriptors for HRI applications, pp. 25-35, (2011).

[5] M. Akhloufi , A. Bendada , “Probabilistic Bayesian framework for infrared face recognition,” World Academy of Science, Engineering and Technology, Vol. 60, pp. 66-70, (2009).

[6] I. Oz and M. M. Khan, “Efficacy of biophysiological measurements at ftfps for facial expression classification: A validation,” in 2012 IEEE-EMBS International Conference on Biomedical and Health Informatics, pp. 108–111, (2012).

[7] L. Trujillo, G. Olague, R. Hammoud, and B. Hernandez, “Automatic feature localization in thermal images for facial expression recognition,” in CVPR Workshops IEEE, pp. 14–14, (2005).

[8] H. S. Bhatt, R. Singh, M. Vatsa, and N. Ratha, “Matching Cross-Resolution Face Images Using Co-Transfer Learning,” IEEE ICIP, (2012).

[9] Z. Wu, M. Peng, and T. Chen, “Thermal face recognition using convolutional neural network,” IEEE International Conference on Optoelectronics and Image Processing, (2016).

[10] Y. Bi, M. Lv, Y. Wei, N. Guan, W. Yi, “Multi-feature fusion for thermal face recogni-tion,” Infrared Physics & Technology, Volume 77, Pages 366-374 July (2016).

[11] A. Nabatchian, E. Abdel-Raheem, and M. Ahmadi, “Human face recognition using different moment invariants: A comparative study,” in Proceedings of the Congress on Image and Signal Processing, pp. 661–6, (2008).

[12] T. Suk, and J. Flusser, “Affine moment invariants generated by automated solution of the equations,” in Proceedings of the 19th International Conference on Pattern Recognition ICPR’08 (Tampa, Florida), (2008).

[13] N. Zaeri, “Pose Invariant Thermal Face Recognition Using AMI Moments,” UKSim- AMSS 18th International Conference on Computer Modelling and Simulation, (2016).

[14] G. H. Vigneau, J. L. Verdugo, G. F. Castro, “Thermal Face Recognition Under Temporal Variation Conditions,” IEEE Access, Vol.: 5, DOI: 10.1109/ACCESS.2017.2704296, pp. 9663 – 9672, (2017).

[15] P. Liu and L. Yin, “Spontaneous thermal facial expression analysis based on trajectory-pooled fisher vector descriptor,” IEEE International Conference on Multimedia and Expo (ICME), pp. 835 – 840, (2017).