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Thermal Images for Face Recognition Using Statistical Analysis

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Abstract—**Despite successes in indoor access control applications, imaging in the visible spectrum demonstrates difficulties in recognizing the faces in varying illumination conditions. Face recognition using different imaging modalities, particularly infrared imaging sensors, has become an area of growing interest. The use of thermal infrared images can improve the performance of face recognition in uncontrolled illumination conditions. In this paper, we present a new technique for face recognition by calculating statistical parameters of component-based thermal images. We propose a feature vector that consists of the following different feature parameters: the first moment, the second moment, and the thermal image histogram. The calculation of these parameters is implemented at the component level, beside the whole face image. The features used in the local analysis are less sensitive to illumination changes, easier for estimating the rotations, have less computational burden, and have the potential to achieve higher correct recognition rates. Hence, the proposed system exploits the advantages and the characteristics of: thermal images, component-based approach, and the statistical features. The experimental results reveal that the new system can achieve a success rate of 94.2% when implemented on the AIAOU Database.**

Keywords-thermal image; face recognition; histogram analysis; moments

I. INTRODUCTION

Research into several biometric modalities including face, fingerprint, iris, and retina recognition has produced varying degrees of success [1]. Face recognition stands as the most appealing modality, since it is the natural mode of identification among humans and does not need to interrupt user activities. At the same time, however, it is one of the most challenging modalities [2]. Despite successes in indoor access control applications, imaging in the visible spectrum demonstrates difficulties in recognizing the faces in varying illumination conditions. Face recognition based only on the visible spectrum has shown difficulties in performing consistently in uncontrolled operating conditions [3]. Since the face is essentially a three-dimensional object, lighting sources from different directions may significantly change visual appearances. This is one of the primary reasons why current face recognition technology is often constrained to indoor access control applications where illumination is well controlled. Light reflected from human faces also varies depending on the skin color 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.

Face recognition using different imaging modalities, particularly infrared (IR) imaging sensors, has become an area of growing interest [4, 5]. The use of thermal IR images can improve the performance of face recognition in uncontrolled illumination conditions [6]. IR cameras provide a measure of thermal emissivity from the facial surface and their images are relatively stable under illumination variation. The anatomical information which is imaged by infrared technology involves subsurface features believed to be unique to each person [2], though the twin's images are not necessarily substantially different. Those features may be imaged at a distance, using passive infrared sensor technology, with or without the cooperation of the subject. IR therefore provides a capability for identification under various lighting conditions including total darkness [3]. The other advantage is that this information is very difficult to be altered purposefully. Thermal IR spectrum that comprises mid-wave IR (3–5 μm) and long-wave IR (8–12 μm) bands are used as source of information for face detection and recognition. Thermal IR sensors measure the emitted heat energy, not reflected, from the object.

In this paper, we present a new technique for face recognition using statistical features of component-based thermal images. We combine the statistical characteristics of the different face image components to produce an integrated result that is enhanced in terms of information content for pattern recognition and classification. Local representations offer robustness against variability due to the changes in localized regions of the objects. The features used in the local feature analysis methods are less sensitive to illumination changes, easier for estimating the rotations, and have less computational burden. Hence, the proposed system exploits the advantages and the characteristics of thermal images, component-based approach, and the statistical features. The evaluation used a database of thermal IR face images that has been recently developed at the Artificial Intelligence laboratory – Arab Open University (AIAOU Database) [7]. The rest of the paper is organized as follows. A brief literature review is given in section 2. Section 3 discusses the new proposed method. A description of the system and the new database is given in section 4. The experimental results and analysis are given in section 5. Finally, conclusion is given in section 6.

II. Literature Review

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 entails 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 [8]. Due to its physiology, a human face consists of "hot" parts that correspond to tissue areas that are rich in vasculature and "cold" parts that correspond to tissue areas with sparse vasculature. Every living and non-living object at a finite temperature emits radiations, which can be captured by infrared cameras. Early studies by Socolinsky *et al.* in [9, 10] suggest that long-wave infrared imagery of human faces is not only a valid biometric, but superior to using comparable visible-light imagery. Prokoski *et al.* [5] anticipated the possibility of extracting the vascular network from thermal facial images and using it as a feature space for face recognition. However, they did not present an algorithmic approach for achieving this.

Authors in [12] 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 which generate a final geometrical transformation that relates the vascular networks. A combination of principal component analysis technique and a Bayesian Maximum Likelihood for thermal face image classification was proposed in [13]. The Bayesian approach uses a probabilistic measure of similarity based on a Bayesian Maximum Likelihood analysis of image differences. Bhowmik *et al.* [14] introduced the role of different IR spectrums, their applications, available thermal databases, and some interesting observations. Lu *et al.* [15] provided a study on normalization of infrared facial images resulting from variant ambient temperatures. Three normalization methods were proposed to eliminate the effect of variant ambient temperatures. The experimental results showed that the proposed methods can increase the robustness of infrared face recognition system and improve its performance. Huang *et al.* [16] proposed a method called discriminative spectral regression to map face images into a common discriminative subspace in which robust classification can be achieved. In the proposed method, the subspace learning problem is transformed into a least-square problem. To realize this, they introduced two regularization terms which reflect the category relationships among data into the least squares approach. Nicolo and Schmid [17] presented a cross-spectral face recognition scheme that encodes images filtered with a bank of Gabor filters followed by three local operators.

Guzman *et al.* [18] discussed a thermal imaging framework that consolidates the steps of feature extraction through the use of morphological operators and registration using the linear image registration tool. The matching showed an average accuracy of 88.46% for skeletonized signatures and 90.39% for anisotropically diffused signatures. Poursaberi *et al.* [19] developed a concept for decision-making support in biometric-based situational awareness systems. Such systems assist users in gathering and analyzing biometric data, and support the decision-making on the human behavioral pattern and/or authentication. As an example, the authors considered a facial biometric assistant that is based on multi-spectral biometrics in visible and infrared bands.

On the other hand, and at the level of component-based face recognition techniques, authors in [20] demonstrated two local nonlinear techniques that are implemented for multispectral face recognition: linear graph embedding and locality preserving projection. The aim of these techniques is to represent the data in a lower dimensional subspace while preserving the local structure of the original image space. Tongzhou *et al*. [21] divided each original image sample into a certain number of subimages, where all the training subimages from the same position constructed a series of new training sub-pattern sets, and the PCA followed by Gabor wavelet were used to extract local projection sub-feature vectors to obtain a set of projection sub-spaces. Zaeri *et al.* [22] have applied a component-based linear discriminant analysis approach to systems requiring high-speed performance. The proposed method enhanced the performance of the system and achieved high recognition rates. Also, we have recently discussed the feasibility of a new idea for face recognition in visible spectrum at the component level [23]. Motivated by the abovementioned discussion and by the results we have obtained from our previous works in the visible spectrum, we propose a new face recognition system that exploits the advantages and the characteristics of thermal images, component-based approach, and statistical features.

III. Thermal Image Histogram

The histogram of a thermal image (similar to a digital one) with temperature levels in the range $[0, L-1]$ is a discrete function $h(r_k) = n_k$, where r_k is the kth temperature value and n_k is the number of "pixels" in the image with temperature r_k . The histogram can be normalized by dividing each of its components by the total number of pixels in the image, denoted by the product MN, where M and N are the row and column dimensions of the image. Thus, a normalized histogram is given by

$$H = p(r_k) = n_k/MN, \text{ for } k = 0, 1, 2, \ldots, L-1. \quad (1)$$

It is common to consider $p(r_k)$ as an estimate of the probability of occurrence of temperature level r_k in an image.

A plot of $p_r(r_k)$ versus r_k is commonly referred to as a "histogram" or histogram distribution. Histograms provide useful image statistics with distinctive features that can be used for face image recognition. Further, they are simple to calculate in software and also lend themselves to economic hardware implementations, thus making them a popular tool for real-time face recognition.

Moreover, if we let r denote a discrete random variable representing temperature values in the range $[0, L - 1]$, and if we let $p(r_k)$ denote the normalized histogram component corresponding to value r_k, then the nth moment of r about its mean is defined as

$$\mu_n(r) = \sum_{i=0}^{L-1} (r_i - \mu)^n p(r_i) \tag{2}$$

where μ is the mean (average temperature) value of r

$$\mu = \sum_{i=0}^{L-1} r_i p(r_i) \tag{3}$$

This is an important image feature that can be considered as an element in the feature vector that represents the "*center of gravity*" of the face temperature distribution. Another important feature to be considered is the spread of these temperature values across the face image. This is given by the variance (or standard deviation) of this set, which can be obtained from the second moment

$$\sigma^2 = \mu_2(r) = \sum_{i=0}^{L-1} (r_i - \mu)^2 p(r_i) \tag{4}$$

In this paper, we propose a feature vector that consists of the following different statistical parameters: the first moment, the second moment, and the thermal image histogram. The calculations of these parameters are implemented at the component level, beside the whole face image. So, the final feature vector consists of the *local* mean, variance and histogram beside the computation of the *global* mean, variance and histogram over the entire thermal face image. We have utilized the local components of a thermal face image (in addition to the entire image) for recognition, as it is expected to achieve higher correct recognition rates since the variations at the component level are limited when compared to the variations within the entire image. In other word, the local parameters are more powerful in preserving the discriminant features of the image in a neighborhood of a pixel.

If (x, y) denote the coordinates of any pixel in a given image, and if S_{xy} denote a neighborhood (subimage) of a specified size, centered on (x, y), then the mean value of the pixels in this neighborhood is given by

$$\mu_{S_{xy}} = \sum_{i=0}^{L-1} r_i p_{S_{xy}}(r_i) \tag{5}$$

where $p_{S_{xy}}$ is the histogram of the pixels in region S_{xy}. Similarly, the variance of the pixels in the neighborhood is given by

$$\sigma^2_{S_{xy}} = \sum_{i=0}^{L-1} \left(r_i - \mu_{S_{xy}}\right)^2 p_{S_{xy}}(r_i) \tag{6}$$

As before, the local mean is a measure of average temperature in neighborhood S_{xy}, and the local variance is a measure of temperature spread in that neighborhood.

We propose the following scheme in dividing the face image:

a) First, we take the whole image as one component. We denote this component as f_0
b) Second, we take only the center part of the face that consists of the eyes, nose, and mouth. We denote this component of the face as f_1^0
c) Third, we divide the thermal image into four different equal-sized components, and denote them as $f_1^1, \dots, f_1^4$
d) Fourth, we divide the thermal image into 16 different equal-sized components, and denote them as $f_2^1, f_2^2, f_2^3, \dots, f_2^{16}$

Then, we find the average temperature, the variance, and the histogram distribution for every component as described above. Finally, we form the feature vector for every image as follow:

$$y = [f_0, f_1^0, f_1^1, \dots, f_1^4, f_2^1, f_2^2, f_2^3, \dots, f_2^{16}]^T \tag{7}$$

where T denotes the transpose, and f_i^j is defined as follows:

$$f_i^j = [\mu_i^j, \sigma^{2}{}_i^j, H_i^j]^T \tag{8}$$

where μ_i^j is the average temperature for the corresponding component as defined in equation (5), and $\sigma^{2}{}_i^j$ is the corresponding variance as defined in equation (6). H_i^j is defined by equation (1). Similarly, f_0 is given by $[\mu_i^g, \sigma^{2}{}_i^g, H_i^g]^T$, where $g \triangleq global$, refers to the thermal face image as a whole and $\mu_i^g, \sigma^{2}{}_i^g, H_i^g$ are found using equations (3), (4), and (1), respectively. The Euclidean distance (L_2 norm) is used as the system classifier, and is given by,

$$D(\mathbf{a}, \mathbf{b}) = \left(\sum_{k=1}^{d} (a_k - b_k)^2\right)^{1/2} \tag{9}$$

for vectors **a** and **b** both of d dimensions. Fig. 1 details the proposed technique.

IV. AIAOU SYSTEM DESCRIPTION AND SETUP

To capture the thermal images, we have utilized the Infrared Camera ETIP 7320 (Fig. 2) which includes a state of the art thermal infrared imaging radiometer. The core technology used in the system is a sophisticated thermal imaging technology using a micro-bolometer 320×240 focal plane array, Vanadium Oxide technology base ensuring very high efficient thermal and spatial resolution. The camera technical specifications are given in Table 1.

We have built a database of 570 images for 19 different subjects taken at different sessions. The database consists of male and female coming from various ethnic backgrounds. Acquisitions were held at different times and most subjects participated in multiple sessions. Infrared images were acquired in the 7.0–14.0 µm range and consist of an uncooled focal plane array incorporating a 320×240 matrix of microbolometer detectors, as specified by the camera specifications detailed in Table 1. Examples of thermal images from the AIAOU database for different subjects are shown in Fig. 3. Each face-recognition experiment is characterized by three image sets:

a) The training set: used to train the face space system in which the recognition is performed.
b) The gallery set: contains the set of ‘‘enrolled’’ images of the subjects to be recognized, where each image is uniquely associated with the identification of a distinct subject in the set.
c) The probe set: a set of images to be identified via matching against the gallery.

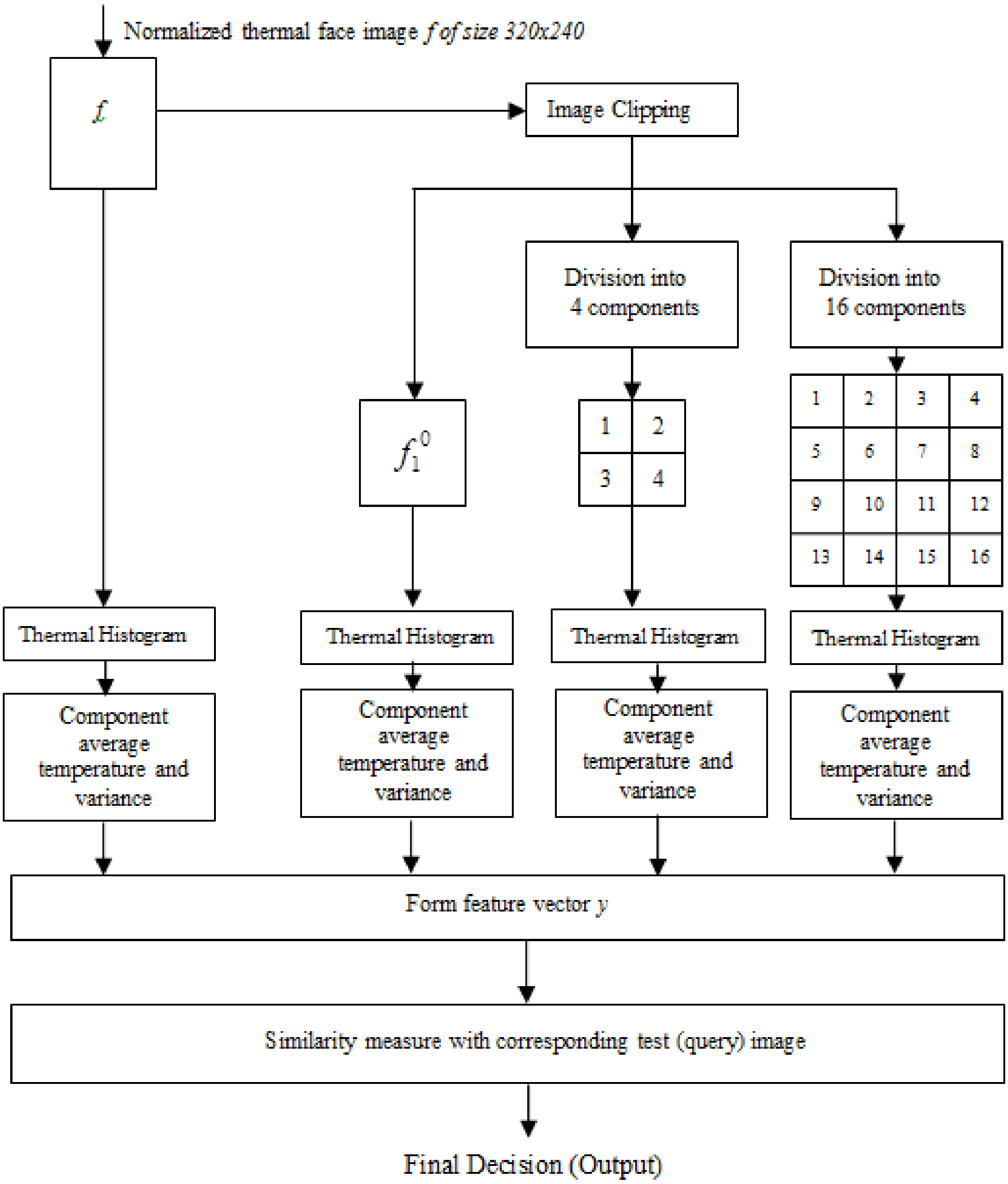

Figure 1. The new proposed technique

Figure 2. Infrared camera ETIP 7320

TABLE I. INFRARED CAMERA ETIP 7320 TECHNICAL SPECIFICATIONS

IR Camera	**Model ICI 7320**
Manufacturer	Infrared Cameras, Inc.
Technology	Microbolometer
Material	Vanadium Oxide
Spectral Response	7-14 µm
Frame Rate	50-60 fps
Array Size	320×240

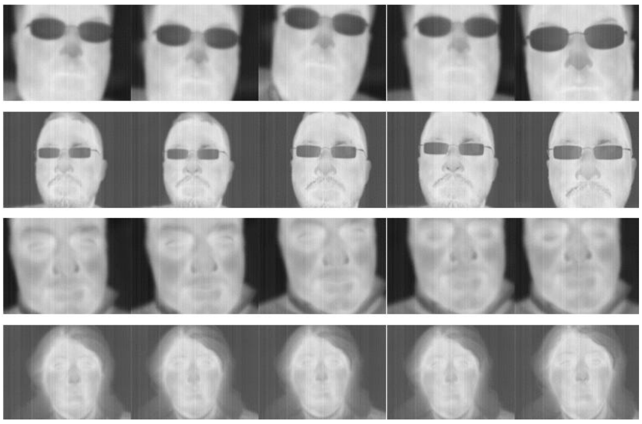

Figure 3. Examples of thermal images from the AIAOU database for different subjects

V. EXPERIMENTAL RESULTS AND ANALYSIS

Before implementing our experiments, we have implemented several pre-processing steps:

a) Integer to float conversion: after the image is read from a file, it is converted to double precision floating point for subsequent image calculations.
b) Geometric normalization: this aligns images such that the faces are of the same size, in the same position, and at the same orientation. Specifically, the image is scaled and rotated to make the eye coordinates coincident with pre-specified locations in the output.
c) Masking: used to eliminate parts of the image of less importance. This is to ensure that the face recognition system does not respond to features corresponding to background, hair, clothing, etc.

Fig. 4 shows histogram distribution for a whole face image for one subject (class) for different number of bins: 20, 50, 100, 200, 300, 400, and 500 bins. Fig. 5 shows the corresponding histograms for another subject. The distinctive and discriminant features between the two figures (subjects) are obvious. The recognition rates for the different number of bins are recorded in Fig. 6. As can be seen from the figure, the rank 1 recognition rate was minimum when the number of bins was 20 with a success rate equals to 83.6%. The recognition rate increases as the number of bins increases and reaches 94.2% when the number of bins equals to 500. We have noticed that the success rate saturates as the number of bins becomes greater than 500.

Another method to evaluate the potential performance of the recognition system is the Cumulative Match Score curve (CMS). The CMS illustrates the trade-off of true positive versus false positive results. The Y-axis is the true positive rate, and the X-axis is the cumulative rank. We can think of the X-axis as the maximum number of images that the system is allowed to report when giving an alarm for a given probe. If the system is allowed to report a larger number of possible matches, the true positive rate generally increases. The results of the CMS evaluation are shown in Fig. 7. Identification is regarded as correct if the true object is in the top rank *n* matches, with rank 1 being the best match.

VI. CONCLUSION

Face recognition using infrared imaging sensors has become an area of growing interest. The use of thermal IR images can improve the performance of face recognition in uncontrolled illumination conditions. In this paper, we presented a new technique for face recognition that is based on statistical calculations of thermal image components. Local representations offer robustness against variability due to the changes in localized regions of the faces. The proposed system exploits the advantages and the characteristics of thermal images, component-based approach, and statistical analysis. The proposed feature vector consists of: the first moment, the second moment, and the thermal image histogram, where the calculation of these features is implemented at the component level, beside the whole face image. We have found that the recognition rate increases as the number of histogram bins increases. The best success rate we obtained was 94.2% when the number of bins was equal to 500.

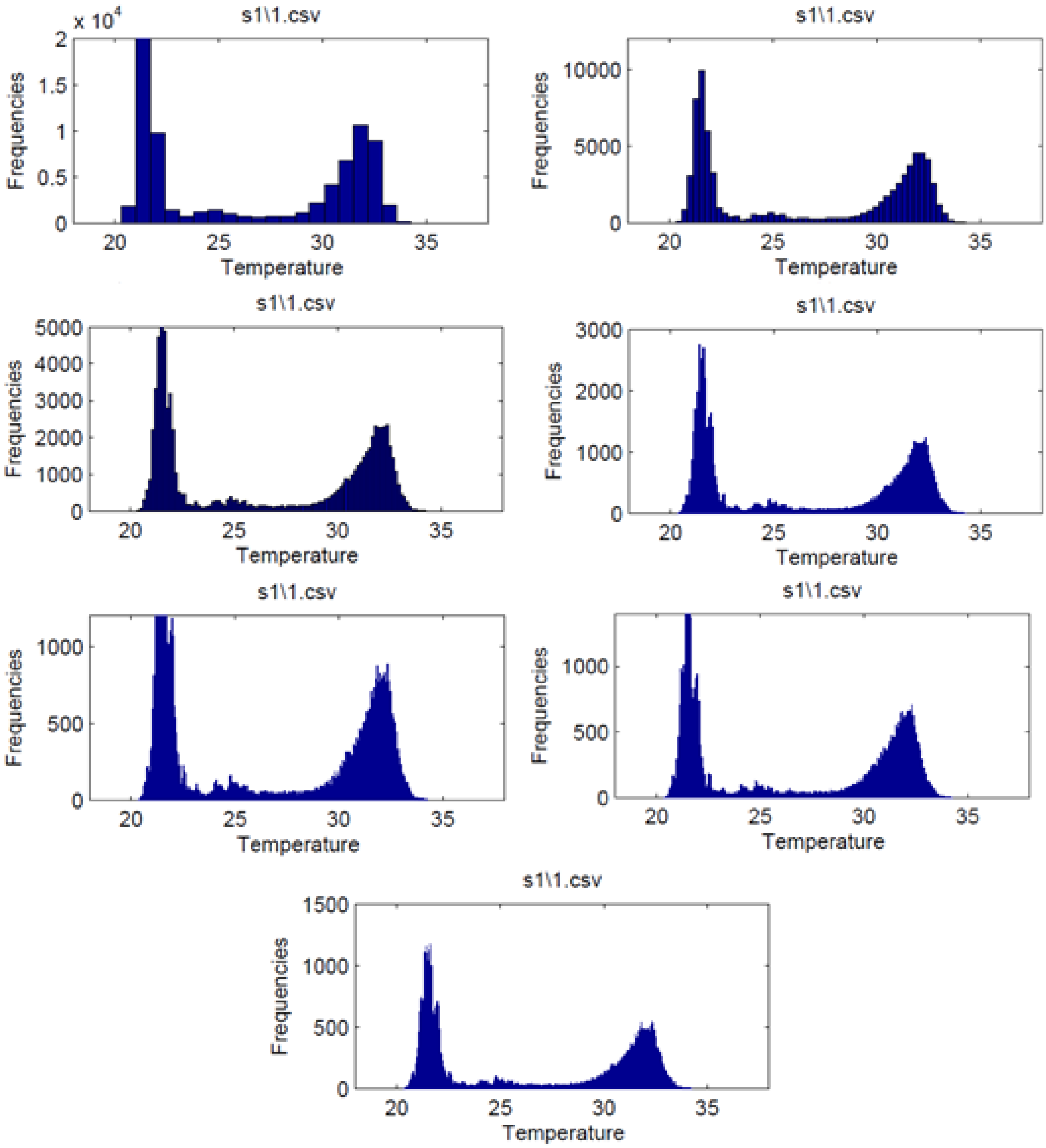

Figure 4. Histogram distribution for a whole face image for one subject (class) for different number of bins: 20, 50, 100, 200, 300, 400, and 500 bins

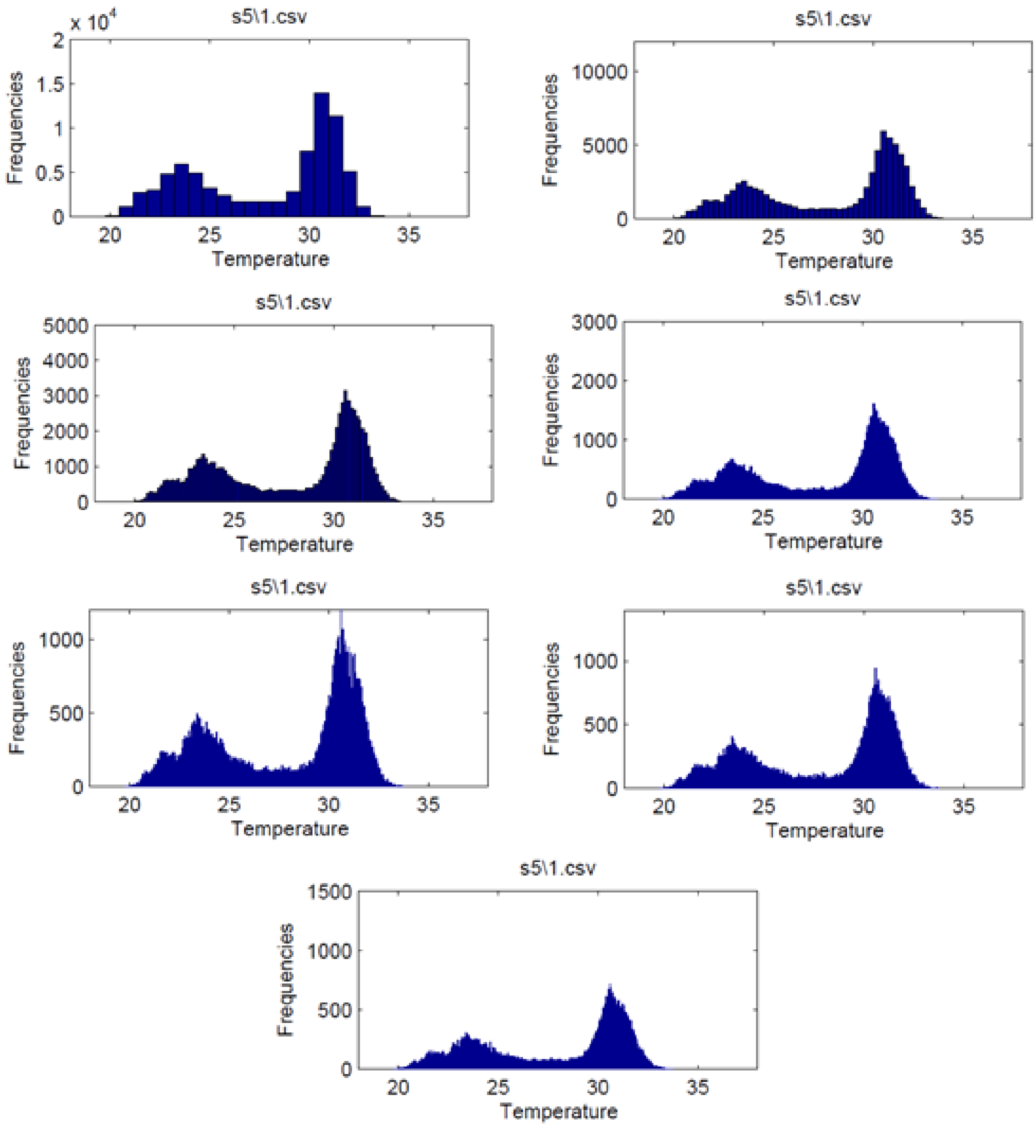

Figure 5. Histogram distribution for a whole face image for another subject (class) for the same number of bins as described in Figure 4

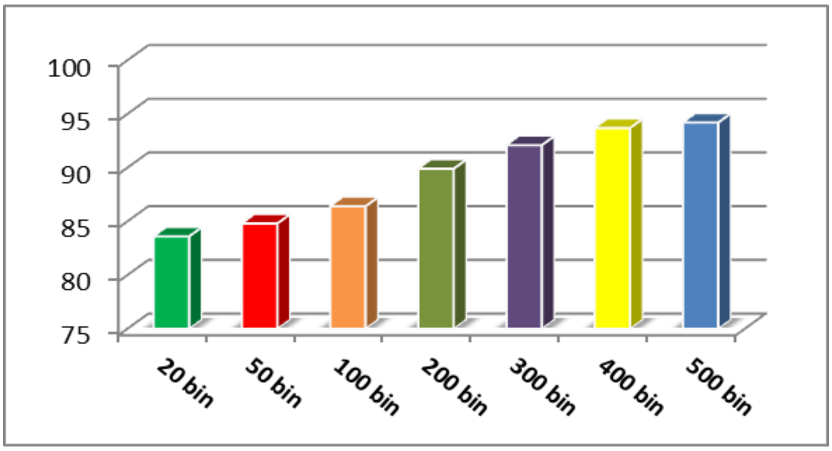

Figure 6. Recognition rates for different number of bins

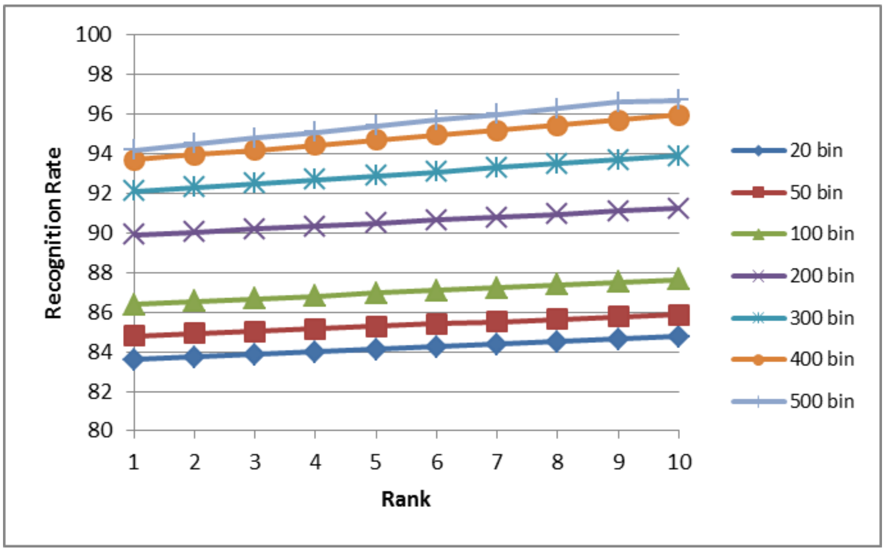

Figure 7. The results of the CMS evaluation for different number of bins

REFERENCES

[1] X. Chen, P. J. Flynn, and K. W. Bowyer, "IR and visible light face recognition", Computer Vision and Image Understanding vol. 99, 2005, pp. 332–358

[2] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld, "Face recognition: A literature survey," ACM Computing Surveys vol. 35 no. 4, 2003, pp. 399–458.

[3] S. G. Kong et al., "Multiscale fusion of visible and thermal ir images for illumination-invariant face recognition," International Journal of Computer Vision, Special Issue on Object Tracking and Classification Beyond the Visible Spectrum, vol. 71, no. 2, 2007, pp. 215-233.

[4] Y. Yoshitomi, T. Miyaura, S. Tomita, and S. Kimura, "Face identification using thermal image processing," in Proceedings of IEEE Int'l Workshop on Robot and Human Communication, 1997, pp. 374–379.

[5] F. Prokoski, "History, Current Status, and Future of Infrared Identification," in Proceedings of IEEE Workshop on Computer Vision Beyond the Visible Spectrum: Methods and Applications, 2000, pp. 514-518.

[6] L.B. Wolff, D.A. Socolinsky, and C.K. Eveland, Face Recognition in the Thermal Infrared, Computer Vision Beyond the Visible Spectrum Book, Springer London, 2006, pp. 167-191.

[7] http://www.aou.edu.kw

[8] C. San Martin, P. Meza, S. Torres, and R. Carrillo, Improved Infrared Face Identification Performance Using Nonuniformity Correction Techniques. Lecture Notes on Computer Science, LNCS 5259, 2008, pp. 1115-1123.

[9] D. Socolinsky and A. Selinger, "A Comparative Analysis of Face Recognition Performance with Visible and Thermal Infrared Imagery," in Proceedings of the 16Th International Conference on Pattern Recognition, 2002, pp. 217-221.

[10] D. A. Socolinsky and A. Selinger, "Thermal face recognition in an operational scenario," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, 2004, pp. 1012-1019.

[11] A. Selinger and D. Socolinsky, "Face recognition in the dark," in Proceedings of Computer Vision and Pattern Recognition Workshop, vol. 8, 2004, pp. 129–134.

[12] G. Hermosilla, P. Loncomilla, J. Ruiz-del-Solar, "Thermal face recognition using local interest points and descriptors for HRI applications", RoboCup 2010: Robot Soccer World Cup XIV, Lecture Notes in Computer Science, vol. 6556, 2011, pp. 25-35.

[13] M. A. Akhloufi and A. Bendada, "Probabilistic Bayesian framework for infrared face recognition," World Academy of Science, Engineering and Technology, 2009.

[14] M. Bhowmik et al., Thermal Infrared Face Recognition – A Biometric Identification Technique for Robust Security system, Reviews, Refinements and New Ideas in Face Recognition, Dr. Peter Corcoran (Ed.), ISBN: 978-953-307-368-2, InTech, DOI: 10.5772/18986, 2011.

[15] Y. Lu, J. Yang, S. Wu, Z. Fang and Z. Xie, Normalization of Infrared Facial Images under Variant Ambient Temperatures, Advanced Biometric Technologies, Dr. Girija Chetty (Ed.), ISBN: 978-953-307-487-0, InTech, DOI: 10.5772/21502, 2011.

[16] X. Huang, Z. Lei; M. Fan; and X. Wang, "Regularized discriminative spectral regression method for heterogeneous face matching", IEEE Transactions on Image Processing, vol. 22 , no. 1, 2013, pp. 353 – 362.

[17] F. Nicolo and N.A. Schmid, "Long range cross-spectral face recognition: Matching SWIR against visible light images," IEEE Transactions on Information Forensics and Security, vol.7, no. 6, 2012, pp. 1717 – 1726.

[18] A. Guzman et al., "Thermal imaging as a biometrics approach to facial signature authentication", IEEE Journal of Biomedical and Health Informatics, vol. 17, no. 1, 2013, pp. 214 – 222.

[19] A. Poursaberi et al.,"Facial biometrics for situational awareness systems," Biometrics, IET, vol. 2, no. 2, 2013, pp. 35 – 47.

[20] M. Akhloufi and A. Bendada, "Multispectral infrared face recognition: a comparative study," 10th International Conference on Quantitative InfraRed Thermography, 2010.

[21] Z. Tongzhou, L. Jin, A. Zelin, C. Nian, and M. Hui, "New image fusion-based algorithm to face recognition", 3rd International Conference on Multimedia and Ubiquitous Engineering, 2009.

[22] N. Zaeri, J. Kittler, and A. Cherri, "Efficient component-based face recognition system for high speed devices," International Conference on Design and Architectures for Signal and Image Processing, 2008.

[23] N. Zaeri, "Discriminant phase component for face recognition," Journal of Electrical and Computer Engineering, vol. 2012, doi:10.1155/2012/718915, 2012.