

Component-Based Thermal Face Recognition

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 IR images can improve the performance of face recognition in uncontrolled illumination conditions. In this paper, we present a component-based technique for thermal face recognition using statistical analysis. We propose a feature vector that consists of the first moment, second moment, and the thermal image histogram. The calculation of these statistical parameters is implemented to components of different sizes, 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. The experimental results reveal that the new system can achieve a success rate of 94.2% when implemented on the AIAOU Database.

Keywords: *Face recognition, thermal image, feature extraction, histogram distribution*

1. 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. Despite successes in indoor access control applications, imaging in the visible spectrum demonstrates difficulties in recognizing the faces in varying illumination conditions, especially under total darkness conditions [2]. 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. 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. 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-

35 wave IR (8–12 μm) bands are used as source of information for face detection and
 36 recognition. Thermal IR sensors measure the emitted heat energy, not reflected, from the
 37 object. IR energy can be viewed in any light conditions and is less subject to scattering and
 38 absorption by smoke or dust than visible light.

39 In this paper, we present a new technique for face recognition that exploits the local
 40 characteristics of the thermal image. The “*whole*” face image is divided to components of
 41 different sizes. The statistical features of these components, beside the “*whole*” image, are
 42 combined together using data fusion. Data fusion finds a combination of multiple statistical
 43 patterns to produce an integrated result that is enhanced in terms of information content for
 44 pattern recognition and classification. Local representations offer robustness against
 45 variability due to the changes in localized regions of the objects. The features used in the
 46 local feature analysis methods are less sensitive to illumination changes, easier for
 47 estimating the rotations, and have less computational burden. Hence, the proposed system
 48 employs the advantages and the characteristics of: thermal images, component-based
 49 approach, and the statistical features. The evaluation used a database of thermal IR face
 50 images that has been recently developed by the Artificial Intelligence laboratory at the Arab
 51 Open University (AIAOU Database) [7]. The organization of the paper is as follows. A brief
 52 literature review is given in section 2. Section 3 discusses the new proposed method. A brief
 53 description of the system is given in section 4. The experimental results and analysis are
 54 discussed in section 5. Finally, the paper is brought to conclusion in section 6.

55 56 2. LITERATURE REVIEW

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 58 In thermal imagery of human tissue the major blood vessels have weak sigmoid edges. This
 59 is due to the natural phenomenon of heat diffusion, which entails that when two objects with
 60 different temperatures are in contact (e.g., vessel and surrounding tissue), heat conduction
 61 creates a smooth temperature gradient at the common boundary [8]. Due to its physiology, a
 62 human face consists of “hot” parts that correspond to tissue areas that are rich in
 63 vasculature and “cold” parts that correspond to tissue areas with sparse vasculature. Every
 64 living and non-living object at a finite temperature emits radiations, which can be captured by
 65 infrared cameras. Early studies by Socolinsky et al. in [9, 10] suggest that long-wave infrared
 66 imagery of human faces is not only a valid biometric, but superior to using comparable
 67 visible-light imagery. However, the testing set size in these studies is relatively small, the
 68 training and gallery are composed of disjoint sets of images of the same subjects, and there
 69 is no substantial time lapse between gallery and probe image acquisition. Prokoski et al. [5]
 70 anticipated the possibility of extracting the vascular network from thermal facial images and
 71 using it as a feature space for face recognition. However, they did not present an algorithmic
 72 approach for achieving this.

73 Authors in [12] proposed an approach using wide-baseline matching of face vascular
 74 networks obtained from thermal images. The vascular networks are obtained through skin
 75 segmentation and morphological operators. The image matching stage uses SIFT
 76 descriptors for verifying correspondences and generating a final geometrical transformation
 77 that relates the vascular networks. A combination of principal component analysis technique
 78 and a Bayesian Maximum Likelihood for thermal face image classification was proposed in
 79 [13]. The Bayesian approach uses a probabilistic measure of similarity based on a Bayesian
 80 Maximum Likelihood analysis of image differences. Bhowmik et al. [14] introduced the role of
 81 different IR spectrums, their applications, some interesting critical observations, available
 82 thermal databases, review works, some experimental results on thermal faces. Lu et al. [15]
 83 provided a study on normalization of infrared facial images, especially resulting from variant
 84 ambient temperatures. Three normalization methods were proposed to eliminate the effect of
 85 variant ambient temperatures. The experimental results show that the proposed methods

can increase the robustness of infrared face recognition system and greatly improve its performance on time-lapse data. 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 squares 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: Simplified Weber Local Descriptor, Local Binary Pattern, and Generalized Local Binary Pattern.

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 consider a facial biometric assistant that functions 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. These techniques find an embedding that preserves local information. 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 the statistical features.

3. 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 k^{th} 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

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

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 $p(r_k)$ 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 . The n th moment of r about its mean is defined as

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

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

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

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

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

In this paper, we propose a feature vector that consists of the following different feature parameters: first moment, second moment, and the thermal image histogram. The calculation of the first, second moments and the histogram distribution is implemented at the component level, beside the whole face image. The final decision results depend on the *local* mean, variance and histogram beside the computation of the *global* mean, variance and histogram over the entire thermal face image. These local parameters are more powerful in preserving the discriminant features in a neighborhood of a pixel in an image.

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

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

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

$$\sigma_{S_{xy}}^2 = \sum_{i=0}^{L-1} (r_i - \mu_{S_{xy}})^2 p_{S_{xy}}(r_i) \quad (6)$$

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:

- First, we take the whole image as one component. We denote this component as f_0
- 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

- 172 c) Third, we divide the thermal image into four different equal-sized components, and
 173 denote them as $f_1^4, \dots, f_4^4$
 174 d) Fourth, we divide the thermal image into 16 different equal-sized components, and
 175 denote them as $f_1^{16}, f_2^{16}, f_3^{16}, \dots, f_{16}^{16}$

176 Then, we find the average temperature, the variance, and the histogram distribution for
 177 every component as described above. Finally, the feature vector for every component is
 178 formed as follow:

$$f_i^j = [\mu_i^j, \sigma_i^j, H_i^j]^T \quad (7)$$

179 where T denotes the transpose, μ_i^j is the average temperature for the corresponding
 180 component as defined in equation (5), and σ_i^j is the corresponding variance as defined in
 181 equation (6). H_i^j is defined by equation (1). The Euclidean distance (L_2 norm) is used as the
 182 system classifier, and is given by

$$D(\mathbf{a}, \mathbf{b}) = \left(\sum_{k=1}^d (a_k - b_k)^2 \right)^{1/2} \quad (8)$$

183 for vectors $\mathbf{a}$ and $\mathbf{b}$ both of d dimensions.

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185 The results obtained from the similarity measures from the feature vectors for the different
 186 number of components are fused together to achieve the final similarity score. Fusion
 187 techniques exploit synergistic integration of the information obtained from different data
 188 sources or from multiple pattern classifiers to produce a more informative form than the
 189 original, and hence to improve the overall classification accuracy [24]. Fusion methods
 190 include AND fusion, OR fusion, majority voting, and ranked list combination. In our
 191 experiments, we have implemented the AND fusion, as it has proven its superiority among
 192 the other fusion methods [24]. Figure 1 details the proposed technique.

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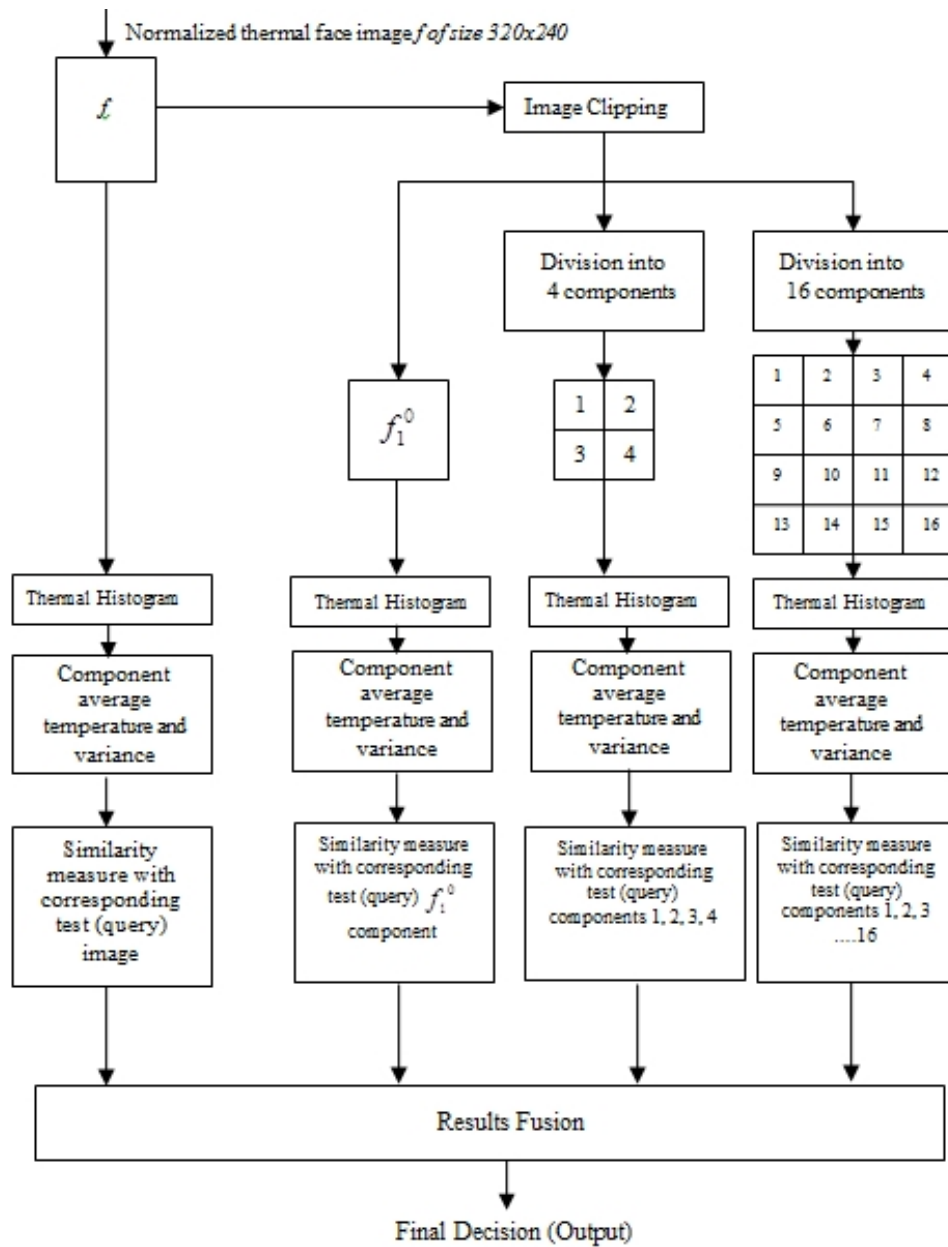


Figure 1. The new proposed technique

4. SYSTEM DESCRIPTION AND SETUP

To capture the thermal images, we have utilized the Infrared Camera ETIP 7320 (Figure 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. 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.

205 Acquisitions were held at different times and most subjects participated in multiple sessions
 206 across a number of different weeks. Infrared images were acquired in the 7.0–14.0 μm
 207 range and consist of an uncooled focal plane array incorporating a 320×240 matrix of
 208 microbolometer detectors, as specified by the camera specifications detailed in Table 1.
 209 Examples of thermal images from the AIAOU database for different subjects are shown in
 210 Figure 3. Each face-recognition experiment is characterized by three image sets:

- 211 a) The training set is used to form a face space in which the recognition is performed.
- 212 b) The gallery set contains the set of “enrolled” images of the subjects to be
 213 recognized, and each image is uniquely associated with the identification of a distinct subject
 214 in the set.
- 215 c) The probe set is a set of images to be identified via matching against the gallery.
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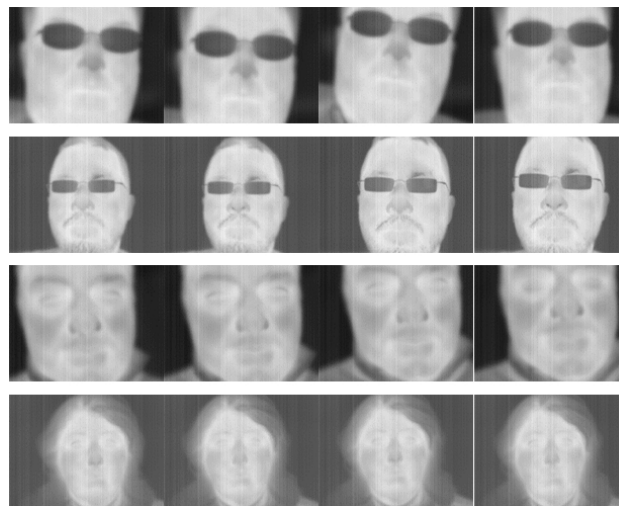


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 219 **Figure 2. Infrared camera ETIP 7320**

220 **Table 1. 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

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

5. 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 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.

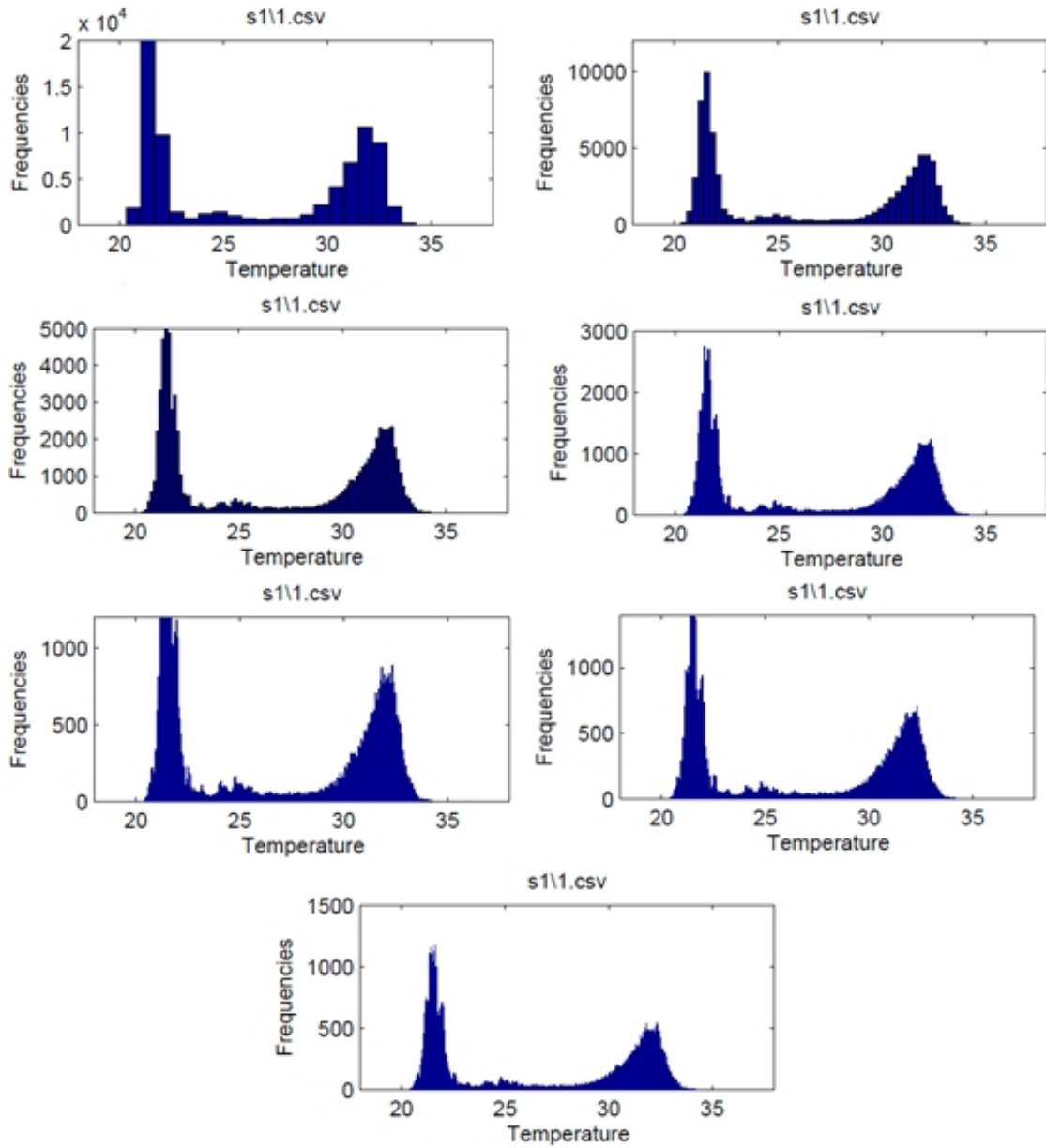
Figure 4 shows histogram distribution of a whole face image for one subject (class) for different number of bins: 20, 50, 100, 200, 300, 400, and 500 bins. Figure 5 shows the corresponding histograms for another subject. The distinctive and discriminant features between the two figures (subjects) are obvious.

In Figure 6, we show the histogram distribution for four different images for the same person (same class) for the case of 20 bins. As can be noticed from the figure, the general characteristics for all the four histograms are similar. Hence, the discriminant features within the class are preserved. Figure 7 shows the histogram distribution for another four different images for another person (class) for the case of 100 bins. Again, this figure shows that the discriminant features for the same class (person) are preserved among the four images. This emphasizes the idea of utilizing this statistical measure as a human identification method.

To further support this idea, we show in Figure 8 the histogram distribution for 10 different persons where each distribution corresponds to a different person (class) for the case of 20 bins. Similarly, Figure 9 shows the results for the case of 100 bins. As we can see from Figures 8 and 9, the discriminant features between classes (that is for different persons) are remarkable and every class can be characterized by its own discriminant features.

The recognition rates for the different number of bins are recorded in Figure 10. 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% for the case of 500 bins. 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 Figure 11, where the performance statistics are reported as cumulative match scores. Identification is regarded as correct if the true object is in the top Rank n matches, with rank 1 being the best match.



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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

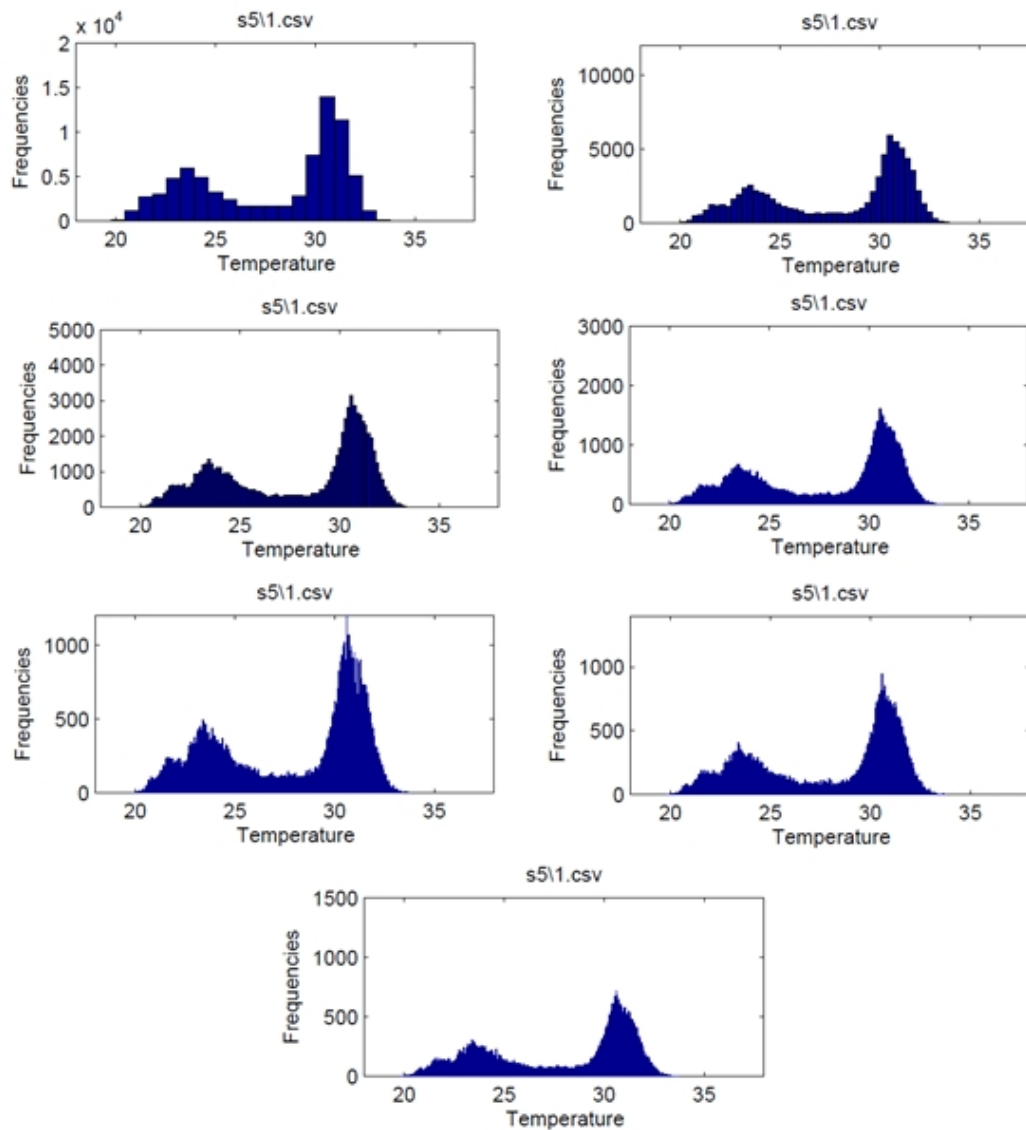


Figure 5. Histogram distribution for a whole face image for another subject (class) for the same number of bins as described in Figure 4

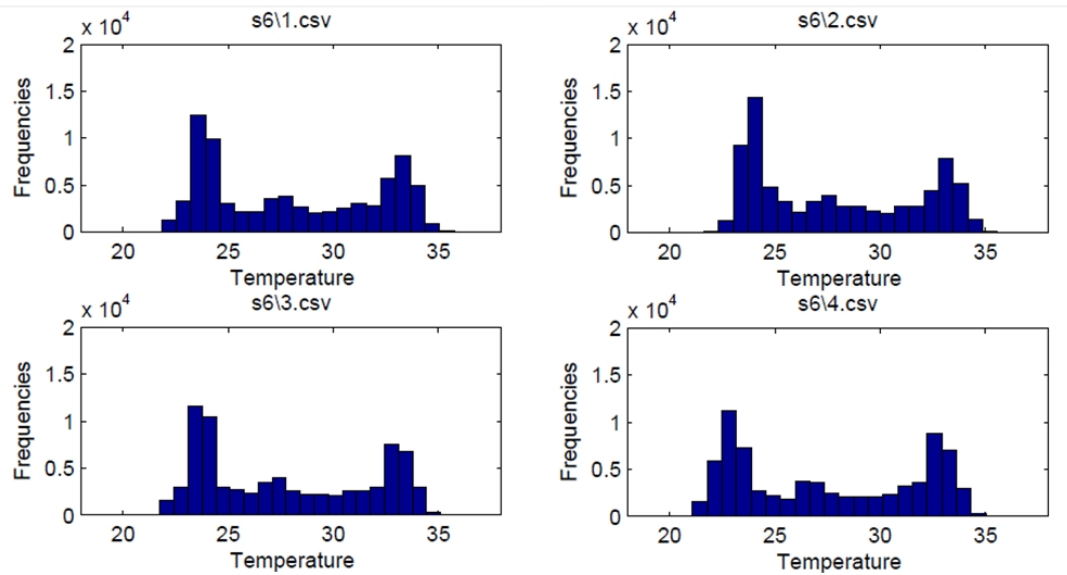


Figure 6. Histogram distribution for four different images for the same person (same class) for the case of 20 bins

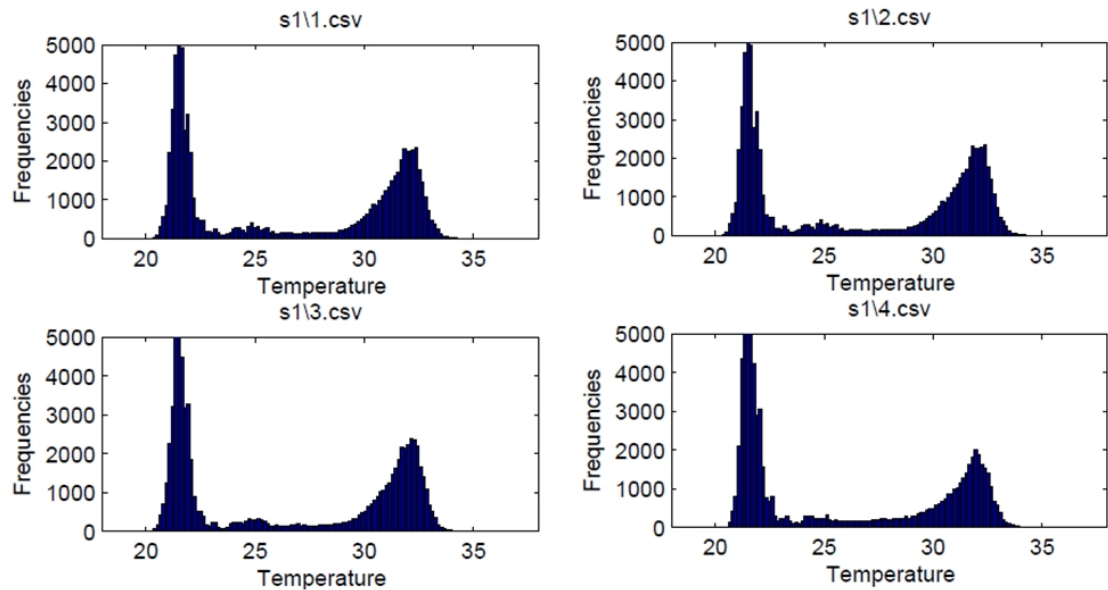
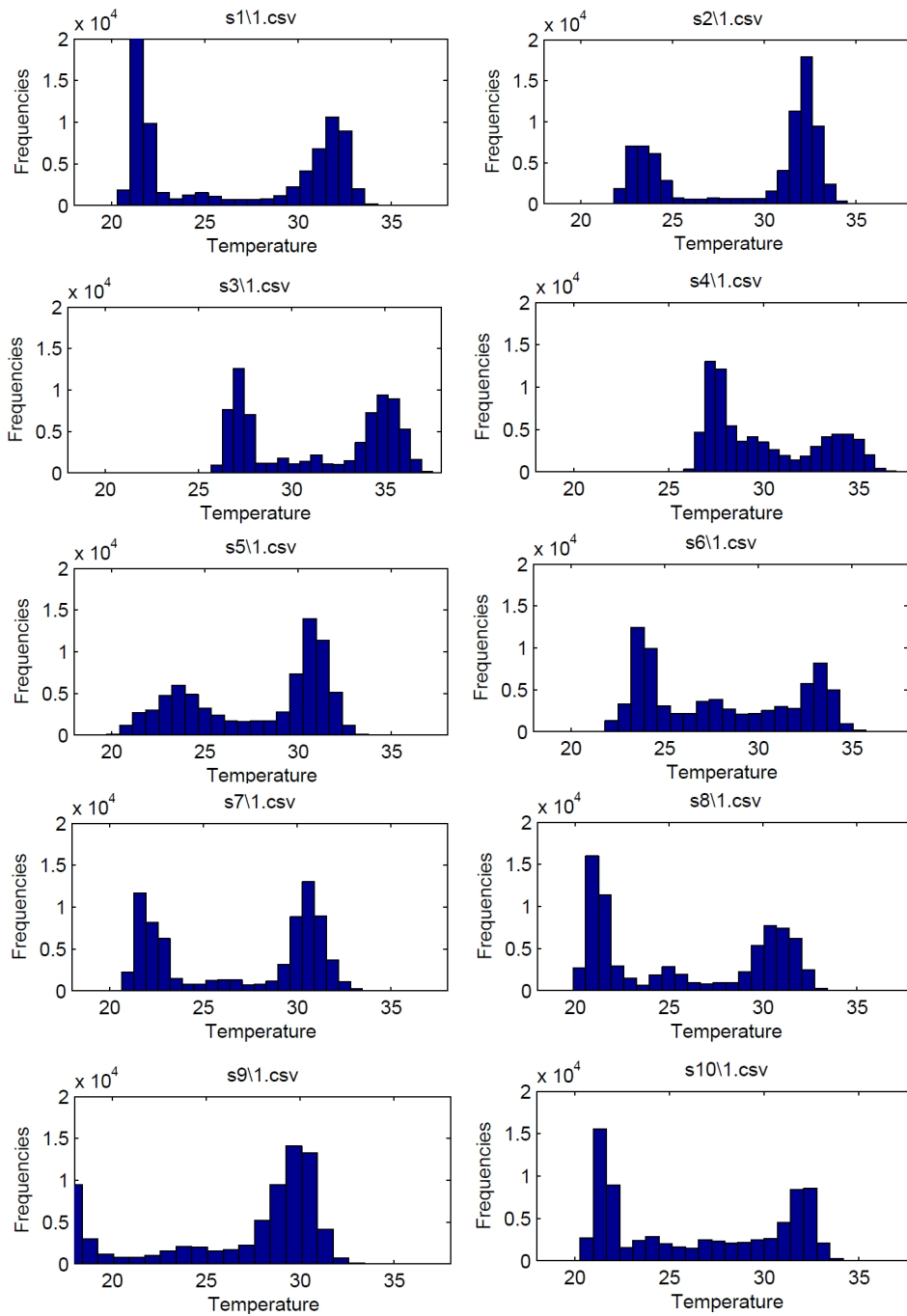


Figure 7. Histogram distribution for another four different images for another person (class) for the case of 100 bins

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Figure 8. Histogram distribution for 10 different persons for the case of 20 bins

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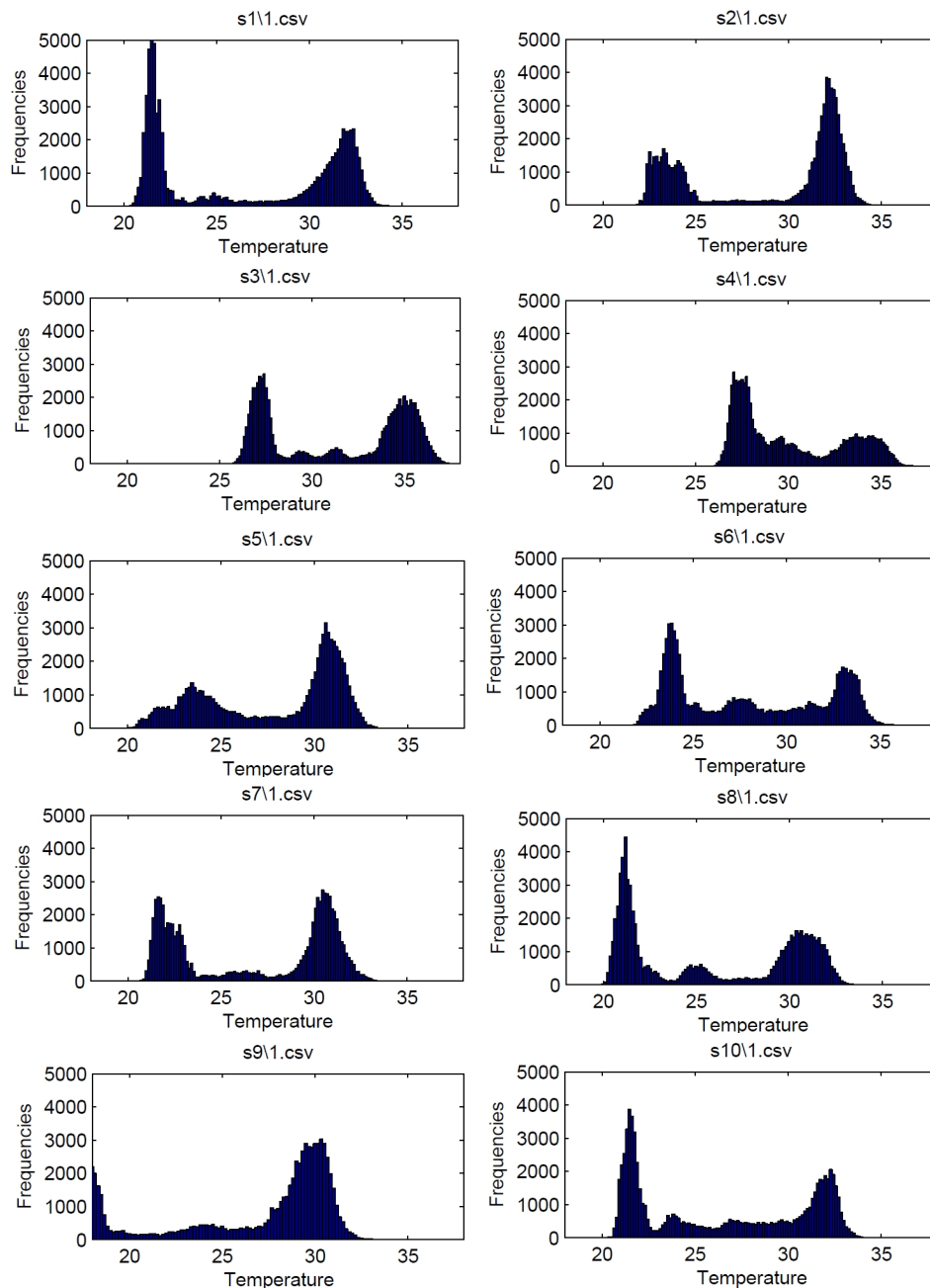
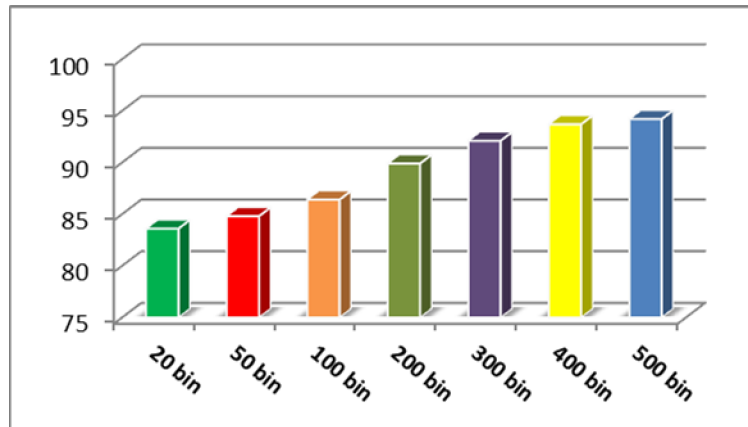


Figure 9. Histogram distribution for 10 different persons for the case of 100 bins

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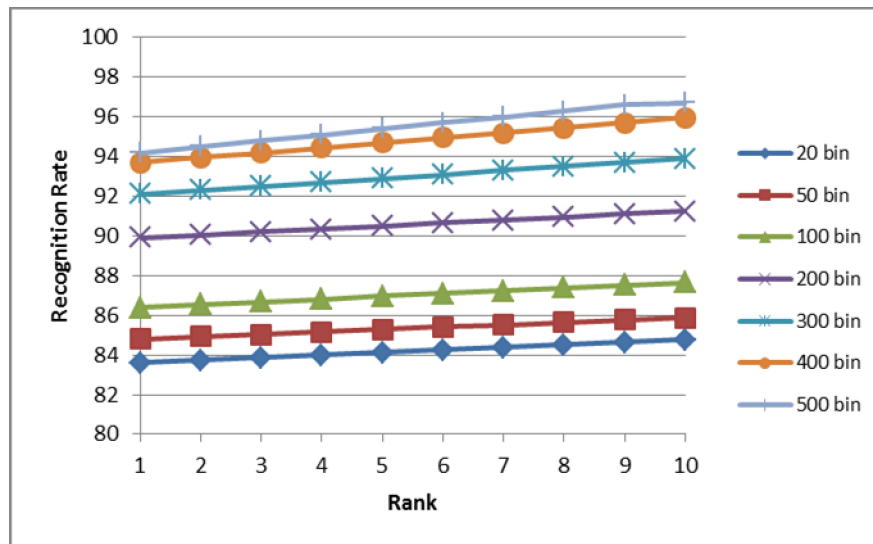


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Figure 10. Recognition rates for different number of bins



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Figure 11. CMS evaluation results for different number of bins

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6. CONCLUSION

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Face recognition using different imaging modalities, particularly 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 using data fusion based on statistical calculations of component-based thermal images. 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 the statistical features. The proposed feature vector consists of: first moment, 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 obtained success rate was 94.2% when the number of bins was equal to 500.

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329 REFERENCES

330

331 [1] Xin Chen *, Patrick J. Flynn, Kevin W. Bowyer, "IR and visible light face recognition",
332 Computer Vision and Image Understanding 99 (2005) 332–358

333 [2] W. Zhao, R. Chellappa, P. J. Phillips, and A. Rosenfeld. Face recognition: A literature
334 survey. ACM Computing Surveys (CSUR), 35(4):399–458, December 2003.

335 [3] Seong G. Kong, Jingu Heo, Faysal Boughorbel, Yue Zheng, Besma R. Abidi, Andreas
336 Koschan, Mingzhong Yi, And Mongi A. Abidi, "Multiscale Fusion of Visible and Thermal IR
337 Images for Illumination-Invariant Face Recognition," International Journal of Computer
338 Vision, Special Issue on Object Tracking and Classification Beyond the Visible Spectrum,
339 Vol. 71, No. 2, pp. 215-233, Feb. 2007.

340 [4] Yoshitomi, Y., Miyaura, T., Tomita, S., and Kimura, S. 1997. Face identification using
341 thermal image processing. In Proc. IEEE Int'l Workshop on Robot and Human
342 Communication, pp. 374–379.

343 [5] Prokoski F. (2000). History, Current Status, and Future of Infrared Identification,
344 Proceedings of . IEEE Workshop on Computer Vision Beyond the Visible Spectrum:
345 Methods and Applications, pp.514

346 [6] Wolff L.B., Socolinsky D.A. & Eveland C.K. (2006). Face Recognition in the Thermal
347 Infrared, Computer Vision Beyond the Visible Spectrum Book, pp. 167-191, Springer London

348 [7] <http://www.aou.edu.kw>

349 [8] San Martin, C.; Meza, P.; Torres, S. & Carrillo, R. (2008), Improved Infrared Face
350 Identification Performance Using Nonuniformity Correction Techniques. Lecture Notes on
351 Computer Science, LNCS 5259, 1115-1123.

352 [9] Socolinsky, D. & Selinger, A. (2002), A Comparative Analysis of Face Recognition
353 Performance with Visible and Thermal Infrared Imagery. In Icpr'02: Proceedings of the 16Th
354 International Conference on Pattern Recognition, 4, 4.

355 [10] Socolinsky, D. A. & Selinger, A. (2004). Thermal face recognition in an operational
356 scenario, Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, pp.
357 1012-1019, Washington DC, USA, 2004

358 [11] A. Selinger, D. Socolinsky, Face recognition in the dark, in: Conf. on Computer Vision
359 and Pattern Recognition Workshop, vol. 8, 2004, pp. 129–134.

360 [12] G. Hermosilla, P. Loncomilla, J. Ruiz-del-Solar, "Thermal Face Recognition using Local
361 Interest Points and Descriptors for HRI Applications",

362 [13] Moulay A. Akhloufi, and Abdelhakim Bendada, "Probabilistic Bayesian framework for
363 infrared face recognition," World Academy of Science, Engineering and Technology, 2009

364 [14] Mrinal Kanti Bhowmik, Kankan Saha, Sharmistha Majumder, Goutam Majumder, Ashim
365 Saha, Aniruddha Nath Sarma, Debotosh Bhattacharjee, Dipak Kumar Basu and Mita
366 Nasipuri, "Thermal Infrared Face Recognition – a Biometric Identification Technique for
367 Robust Security System,

- 368 [15] Yu Lu, Jucheng Yang, Shiqian Wu, Zhijun Fang and Zhihua Xie, "Normalization of
369 Infrared Facial Images under Variant Ambient Temperatures",
- 370 [16] Xiangsheng Huang ; Zhen Lei ; Mingyu Fan ; Xiao Wang, 'Regularized Discriminative
371 Spectral Regression Method for Heterogeneous Face Matching", Image Processing, IEEE
372 Transactions on (Volume:22 , Issue: 1), Jan. 2013, Page(s): 353 - 362
- 373 [17] Nicolo, F. Schmid, N.A., "Long Range Cross-Spectral Face Recognition: Matching
374 SWIR Against Visible Light Images," Information Forensics and Security, IEEE Transactions
375 on (Volume:7 , Issue: 6), Dec. 2012, Page(s): 1717 - 1726
- 376 [18] Guzman, A. M., Goryawala, M. ; Wang, J. ; Barreto, A. ; Andrian, J. ; Rishe, N. ;
377 Adjouadi, M., "Thermal Imaging as a Biometrics Approach to Facial Signature
378 Authentication", Biomedical and Health Informatics, IEEE Journal of (Volume:17 , Issue: 1),
379 Jan. 2013, Page(s): 214 - 222
- 380 [19] Poursaberi, A., Vana, J. ; Mracek, S. ; Dvora, R. ; Yanushkevich, S.N. ; Drahansky, M. ;
381 Shmerko, V.P. ; Gavrilova, M.L., "Facial biometrics for situational awareness systems,"
382 Biometrics, IET (Volume:2 , Issue: 2), June 2013, Page(s): 35 - 47
- 383 [20] M. Akhloufi* and A. Bendada, " Multispectral Infrared Face Recognition: a comparative
384 study," 10th International Conference on Quantitative InfraRed Thermography, Canada
- 385 [21] Zhao Tongzhou, Li Jin, Ai Zelin, Chen Nian, Ming Hui, "New Image Fusion-Based
386 Algorithm to Face Recognition", 3rd International Conference on Multimedia and Ubiquitous
387 Engineering, 2009.
- 388 [22] N. Zaeri, J. Kittler, and A. Cherri, ``Efficient Component-Based Face Recognition
389 System for High Speed Devices," International Conference on Design and Architectures for
390 Signal and Image Processing, Belgium, 2008.
- 391 [23] N. Zaeri, "Discriminant Phase Component for Face Recognition," Journal of Electrical
392 and Computer Engineering, vol. 2012, doi:10.1155/2012/718915, 2012
- 393 [24] N. Poh and J. Kittler, "A Unified Framework for Biometric Expert Fusion Incorporating
394 Quality Measures," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol:34
395 , Issue 1, Page(s):3 – 18, 2012
396