

Component-Based Thermal Face Recognition

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ABSTRACT

Face recognition based only on the visible spectrum has shown difficulties in performing consistently in uncontrolled operating conditions. Face recognition using different imaging modalities, particularly infrared imaging sensors, has become an area of growing interest in recent years. In this paper, we present a new technique for face recognition that exploits the local statistical characteristics of a thermal image. The “whole” face image is divided into components of different sizes. The statistical features of these components, beside the “whole” image, are combined together using fusion methods. Decision level fusion finds a combination of multiple statistical patterns 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 proposed feature vector consists of different moments’ calculations and thermal components’ histograms. The features found from 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 96.4% 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 conditions of varying illumination, 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 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.

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. These 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 it is very difficult to alter this information purposefully. The thermal IR spectrum that comprises mid-wave IR (3–5 μm) and long-wave IR (8–12 μm) bands is used as a source of information for face detection and recognition. Thermal IR sensors measure the heat energy that is emitted, not reflected, from the object. IR energy can be viewed in any light conditions and is less subject to scattering and absorption by smoke or dust than visible light.

In this paper, we present a new technique for face recognition that exploits the local characteristics of the thermal image. The “*whole*” face image is divided into components of different sizes. The statistical features of these components, beside the “*whole*” image are combined using fusion methods. Decision-level fusion finds a combination of multiple statistical patterns 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 employs the advantages and the characteristics of thermal images, component-based approach, the statistical features, and fusion. The evaluation used a database of thermal IR face images that has been recently developed by the Artificial Intelligence laboratory at the Arab Open University (AIAOU Database) [7]. Our work makes the following contributions: First, it proposes a way to achieve thermal face image representation in a simple manner. Second, it utilizes the statistical characteristics of thermal components alongside the advantages of results fusion. Third, it provides a large number of experimental results that show that the proposed method is good enough to recognize a person in a competitive way, especially when considering consumed time and speed. The organization of the paper is as follows. A brief literature review is given in Section 2. Section 3 discusses the proposed new method. A brief description of the system is given in Section 4. The experimental results and analysis are discussed in Section 5. Finally, the paper is brought to a conclusion in Section 6.

2. 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 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 [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 radiation, which can be captured by infrared cameras. Early studies by Socolinsky et al. in [9, 10, 11] suggest that long-wave infrared imagery of human faces is not only a valid biometric, but superior to using comparable visible-light imagery. However, the testing set size in these studies is relatively small, the training and gallery are composed of disjoint sets of images of the same subjects, and there is no substantial time lapse between gallery and probe image acquisition. Prokoski et al. [5] anticipated the possibility of extracting the vascular network from thermal facial

84 images and using it as a feature space for face recognition. However, they did not present
85 an algorithmic approach for achieving this. Authors in [12] proposed an approach using
86 wide-baseline matching of face vascular networks obtained from thermal images. The
87 vascular networks are obtained through skin segmentation and morphological operators.
88 The image matching stage uses SIFT descriptors for verifying correspondences and
89 generating a final geometrical transformation that relates the vascular networks. However,
90 the proposed skin detection model is created by modelling the skin pixel intensity distribution
91 of non-skin intensity distribution as mixture of Gaussians. This is a time- and memory-
92 consuming task. Furthermore, the general parameters for the Gaussians cannot be
93 obtained, as they depend on the response of the particular camera to thermal intensity. The
94 authors have reported a best recognition rate of 95.7% for a small database that consists of
95 156 thermal images. A combination of principal component analysis technique and a
96 Bayesian Maximum Likelihood for thermal face image classification was proposed in [13].
97 The Bayesian approach uses a probabilistic measure of similarity based on a Bayesian
98 Maximum Likelihood analysis of image differences. In this work, the authors have developed
99 nonlinear technique for multispectral face recognition. However, most of the results they
100 have obtained were poor. Bayesian face recognition needs a sufficient number of face
101 images for intrapersonal learning process and if the number of these images is low then the
102 system performance will be inefficient.

103 Bhowmik et al. [14] introduced the role of different IR spectrums and their applications. In
104 their experimental work, they fused both thermal and visible images to enhance the
105 recognition rate, as it is expected that the fusion process improves the overall performance
106 of the system. They tested their method on IRIS and Terravic databases. In both databases,
107 the images were taken in one time session. In other words, the effect of time lapse was not
108 taken into consideration. Lu et al. [15] conducted a study on normalization of infrared facial
109 images, especially those resulting from variant ambient temperatures. Three normalization
110 methods were proposed to eliminate the effect of variant ambient temperatures. The
111 experimental results showed that the proposed methods can increase the robustness of
112 infrared face recognition system and greatly improve its performance on time-lapse data.
113 They recorded a maximum success rate of 89.1% using PCA with weigh coefficient. Huang
114 et al. [16] proposed a method called discriminative spectral regression to map face images
115 from various modalities, such as the visual, the IR modality, and the sketch modality into a
116 common discriminative subspace. They introduced two regularization terms, which reflect
117 the category relationships among data, into the least squares approach where the class
118 information is integrated in the cost function. However, the method does not make use of the
119 discriminative information among images from different classes sufficiently. Its performance
120 can be further improved by introducing the category relationship into its objective function.
121 Also, the proposed model for solving the heterogeneous subspace learning problem cannot
122 be transformed into a matrix optimization which can be solved efficiently. In addition, the
123 proposed variation of the optimization problem is computationally exhaustive. Further, their
124 method was not tested over data sets that contain varying poses or expressions. Nicolo and
125 Schmid [17] presented a cross-spectral face recognition scheme that encodes images
126 filtered with a bank of Gabor filters followed by three local operators: Simplified Weber Local
127 Descriptor, Local Binary Pattern, and Generalized Local Binary Pattern. Both magnitude and
128 phase of filtered images are encoded. The proposed technique can be used in challenging
129 atmospheric conditions such as rain, for and mist. Also, it is applicable to the scenario where
130 no IR data are available to train the recognition system. However, a detailed discussion of
131 the choice of filter parameters was not discussed. Moreover, the efficiency of the technique
132 was compared against one method only.

134 Guzman et al. [18] discussed a thermal imaging framework that consolidates the steps of
135 feature extraction through the use of morphological operators and registration using the
136 linear image registration tool. The matching showed an average accuracy of 88.46% for
137 skeletonized signatures and 90.39% for anisotropically diffused signatures. Poursaberi et al.
138 [19] developed a concept for decision-making support in biometric-based situational
139 awareness systems. Such systems assist users in gathering and analyzing biometric data,
140 and support the decision-making on the human behavioral pattern and/or authentication. As
141 an example, the authors consider a facial biometric assistant that functions based on multi-
142 spectral biometrics in visible and infrared bands. Seal et al. [25] proposed a human face
143 recognition system based on wavelet transform from thermal IR images. Their method
144 utilizes a “Haar” wavelet to extract a low frequency band from the cropped face region, and
145 the classification is based only on low-frequency components. In general, wavelet transform
146 captures both frequency and time (location information). Haar transformation was used
147 because of its simplicity. However, the proposed method in [25] ignores details at different
148 levels, some of which might be of great importance, especially if they contain important
149 discriminant features. The same authors have proposed another work on thermal face
150 recognition based on the use of minutiae points [26]. They suggested that there is an
151 analogy between thermal imprints of human faces and fingerprints of human beings.
152 Thermal imprints of blood vessels may be treated as ridges in fingerprints, and fingerprint
153 recognition techniques may be applied to the thermal imprints of the human faces in order to
154 recognize them. In this work they used three methods to extract the blood perfusion image:
155 bit-plane slicing, morphological erosion, and Sobel edge operators. The computational
156 complexity of the proposed work is relatively large and can be exhaustive if applied on large
157 databases. Authors in [27] proposed using a local binary pattern (LBP) for thermal face
158 recognition. Multilayer feed forward neural network and minimum distance classifier were
159 used to classify face images. The maximum success rate they obtained was ~95% when
160 tested on a locally generated database consisting of 578 images. However, this system is
161 applicable only to front views with constant background. It may fail in unconstrained
162 environments like natural scenes.

163 On the other hand, at the level of component-based face recognition techniques, authors in
164 [20] demonstrated two local nonlinear techniques for face recognition: Linear Graph
165 Embedding and Locality Preserving Projection. These techniques find an embedding that
166 preserves local information. The aim was to represent the data in a lower dimensional
167 subspace while preserving the local structure of the original image space. They have
168 recorded a best recognition rate of 91%. However, their proposed techniques are
169 computationally greedy. Tongzhou et al. [21] divided each original image sample into a
170 certain number of subimages, where all the training subimages from the same position
171 constructed a series of new training sub-pattern sets, and the PCA followed by Gabor
172 wavelet were used to extract local projection sub-feature vectors to obtain a set of projection
173 sub-spaces. Zaeri et al. [22] have applied a component-based linear discriminant analysis
174 approach to systems requiring high-speed performance. The proposed method enhanced
175 the performance of the system and achieved high recognition rates. Recently, a number of
176 learning methods using local transform sparse representation have been proposed in visible
177 spectrum. Xu et al. [28] and Xu et al. [29] have proposed a two-phase test sample sparse
178 representation method. The first phase seeks to represent the test sample as a linear
179 combination of all the training samples and exploits the representation ability of each training
180 sample to determine M “nearest neighbors” for the test sample. The second phase
181 represents the test sample as a linear combination of the determined M nearest neighbors
182 and uses the representation result to perform classification. Similarly, Yang et al. [30] have
183 focused on sparse representation based classification, where they gave a theoretical
184 justification to support the effectiveness of sparse representation-based classifiers. Also, we
185 have recently discussed the feasibility of a new method 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 work in the visible spectrum, we propose a new face recognition system that exploits the advantages and characteristics of both the thermal images approach and the component-based approach.

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 the 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 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 and 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.

227 If (x, y) denote the coordinates of any pixel in a given image, and if S_{xy} denotes a
 228 neighborhood (component) of a specified size, centered on (x, y) , then the mean value of the
 229 pixels in this neighborhood is given by
 230

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

231 where $p_{S_{xy}}$ is the histogram of the pixels in region S_{xy} . Similarly, the variance of the pixels in
 232 the neighborhood is given by
 233

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

234 As before, the local mean is a measure of average temperature in neighborhood S_{xy} , and
 235 the local variance is a measure of temperature spread in that neighborhood.
 236

237 **We propose the following scheme in dividing the face image:**

- 238 a) First, we take the whole image as one component. We denote this component as f_0
- 239 b) Second, we take only the center part of the face that consists of the eyes, nose, and
 240 mouth. We denote this component of the face as f_1^0
- 241 c) Third, we divide the thermal image into four different equal-sized components, and
 242 denote them as $f_2^0, f_2^1, f_2^2, f_2^3$
- 243 d) Fourth, we divide the thermal image into 16 different equal-sized components, and
 244 denote them as $f_3^0, f_3^1, f_3^2, \dots, f_3^{15}$

245 Then, we find the average temperature, the variance, and the histogram distribution for
 246 every component as described above. Finally, the feature vector for every component is
 247 formed as follows:

$$f_i^j = [\mu_i^j, \sigma_i^2, H_i^j]^T \quad (7)$$

248 where T denotes the transpose, μ_i^j is the average temperature for the corresponding
 249 component as defined in equation (5), and σ_i^2 is the corresponding variance as defined in
 250 equation (6). H_i^j is defined by equation (1). The Euclidean distance (L_2 norm) is used as the
 251 system classifier, and is given by

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

252 for vectors $\mathbf{a}$ and $\mathbf{b}$ both of d dimensions.
 253

254 The results obtained from the similarity measures from the feature vectors for the different
 255 number of components are fused together to achieve the final similarity score. Decision-level
 256 fusion combines the results to yield a final fused decision based on a joint assertion of
 257 multiple single source results (or decisions) to achieve an improved classification. Prior
 258 knowledge and domain-specific information can also be incorporated. Fusion techniques
 259 exploit synergistic integration of the information obtained from different data sources or from
 260 multiple pattern classifiers to produce a more detailed form than the original, and hence
 261 improve the overall classification accuracy [24]. Fusion methods include AND fusion, OR
 262 fusion, majority voting, and ranked list combination. In our experiments, we have
 263 implemented AND fusion, as it has proven its superiority among the other fusion methods
 264 [24]. It is worth mentioning that the study of best fusion method is beyond the scope of this
 265 paper. Figure 1 details the proposed technique.
 266

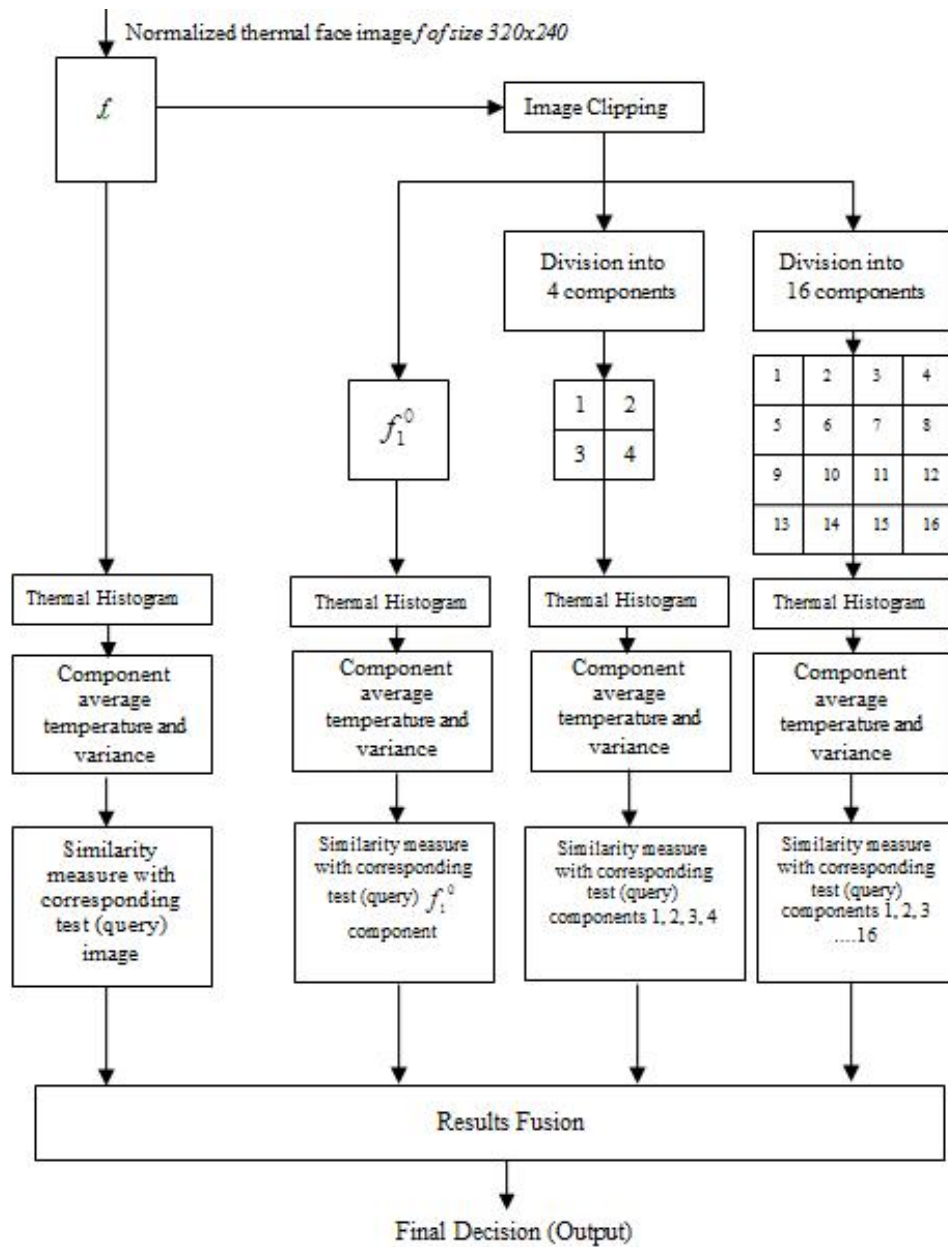


Figure 1. The proposed new technique

4. SYSTEM DESCRIPTION AND SETUP

To capture the thermal images, we used 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 and a Vanadium Oxide technology base, ensuring very high efficient thermal and spatial resolution.

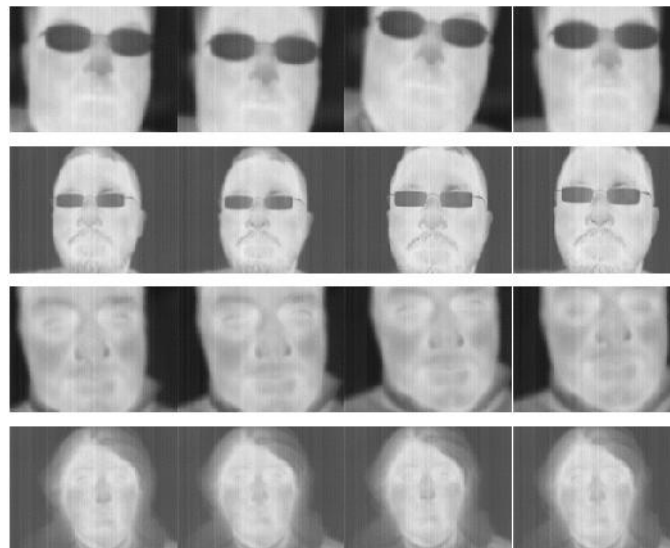
We have built a database of 570 images for 19 different subjects taken in different sessions. The database consists of males and females from various ethnic backgrounds. Acquisitions

278 were held at different times and most subjects participated in multiple sessions across a
279 number of different weeks. Infrared images were acquired in the 7.0–14.0 μm range and
280 consist of an uncooled focal plane array incorporating a 320×240 matrix of microbolometer
281 detectors. Examples of thermal images from the AIAOU database for different subjects are
282 shown in Figure 3. Each face-recognition experiment is characterized by three image sets:

- 283 a) The training set is used to form a face space in which the recognition is performed. This
284 set consists of five images per subject (class). These images were chosen randomly among
285 the 30 available images for each subject.
286 b) The gallery set contains the set of “enrolled” images of the subjects to be recognized, and
287 each image is uniquely associated with the identification of a distinct subject in the set. This
288 set also consists of five images per subject, and were similarly chosen randomly among the
289 30 available images for each subject.
290 c) The probe (testing) set is a set of images to be identified via matching against the gallery.
291 This set consists of 380 images (20 images per subject × 19 subjects).
292
293



294
295 **Figure 2. Infrared camera ETIP 7320**



297
298 **Figure 3. Examples of thermal images from the AIAOU database for different subjects**
299

5. EXPERIMENTAL RESULTS AND ANALYSIS

Before conducting our experiments, we took several pre-processing steps:

- Integer to float conversion: After the image is read from a file, it is converted to double precision floating point for subsequent image calculations.
- 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.
- Masking: This is used to eliminate less important parts of the image, ensuring that the face-recognition system does not respond to features corresponding to background, hair, clothing, etc.

Table 1(a) shows skin mean temperature over each block of the different blocks described in Figure 1, for five different images belonging to the same subject (person). Table 1(b) shows the corresponding values for another person. Similar results are recorded in Table 2 for temperature variance.

Table 1. Skin mean temperature (in degrees Celsius) for each block for different images a) of the same person, b) of another person

	Image 1	Image 2	Image 3	Image 4	Image 5
f_1^0	29.0	29.9	29.1	30.7	30.4
f_2^0	22.9	24.1	28.0	26.0	24.9
f_2^1	23.5	24.2	28.0	26.0	25.1
f_2^2	25.7	27.3	23.6	25.4	25.5
f_2^3	26.7	27.8	23.8	25.7	26.3
f_3^0	19.6	19.7	24.3	21.1	19.8
f_3^1	19.9	20.0	26.0	22.3	20.6
f_3^2	20.2	20.3	25.3	21.9	20.9
f_3^3	20.8	20.6	24.5	21.7	20.4
f_3^4	24.7	27.6	30.8	29.9	28.7
f_3^5	27.5	29.0	31.0	30.7	30.4
f_3^6	27.3	29.1	31.1	30.6	30.3
f_3^7	25.5	26.7	31.2	29.9	28.6
f_3^8	28.9	30.6	25.6	29.3	29.1
f_3^9	30.5	30.7	27.2	30.7	30.5
f_3^{10}	30.8	30.9	27.0	30.9	30.6
f_3^{11}	30.8	31.2	25.6	29.4	30.9
f_3^{12}	20.8	23.0	20.6	20.6	20.5
f_3^{13}	22.7	24.8	20.9	21.2	21.8
f_3^{14}	22.8	25.1	21.1	21.3	22.4
f_3^{15}	22.4	23.8	21.3	21.5	21.4

	Image 1	Image 2	Image 3	Image 4	Image 5
f_1^0	28.3	30.0	30.7	28.3	29.3
f_2^0	26.8	25.3	25.6	26.1	26.5
f_2^1	28.6	27.1	29.6	28.8	29.3
f_2^2	26.5	25.5	25.5	25.1	24.9
f_2^3	29.5	28.0	26.3	26.5	26.3
f_3^0	27.7	22.7	22.3	24.3	24.7
f_3^1	22.3	23.0	24.9	24.1	25.8
f_3^2	25.9	22.1	26.0	25.2	25.5
f_3^3	24.9	22.8	28.1	26.3	27.8
f_3^4	31.5	27.1	24.5	30.4	28.0
f_3^5	25.9	28.3	30.6	25.6	27.4
f_3^6	31.0	31.7	32.1	31.3	31.8
f_3^7	32.6	31.9	32.1	32.4	32.3
f_3^8	30.8	28.9	27.4	31.4	29.9
f_3^9	25.7	28.4	28.9	25.8	27.2
f_3^{10}	30.7	31.7	31.5	30.5	31.1
f_3^{11}	32.4	32.1	31.5	32.0	32.0
f_3^{12}	25.8	22.2	23.1	22.8	21.9
f_3^{13}	23.6	22.6	22.7	20.5	20.6
f_3^{14}	26.9	24.4	22.1	22.4	22.1
f_3^{15}	28.2	23.8	20.0	21.1	20.1

Table 2. Skin temperature variance for each block for different images: a) of the same person, b) of another person

(a)						(b)					
	Image 1	Image 2	Image 3	Image 4	Image 5		Image 1	Image 2	Image 3	Image 4	Image 5
f_1^0	12.60	6.01	13.80	1.79	0.95	f_1^0	5.8	5.8	9.7	9.7	6.0
f_2^0	21.73	25.28	10.04	24.15	27.14	f_2^0	12.6	12.7	15.4	15.5	17.0
f_2^1	19.50	22.93	18.62	22.92	25.99	f_2^1	10.6	11.6	14.1	14.1	15.4
f_2^2	23.89	21.36	18.96	24.59	24.35	f_2^2	11.6	11.5	13.0	12.8	13.2
f_2^3	22.18	20.02	16.20	22.67	23.35	f_2^3	13.9	14.3	14.0	12.7	14.6
f_3^0	0.77	0.73	18.69	3.65	1.50	f_3^0	16.6	17.0	0.3	0.2	7.6
f_3^1	0.21	0.22	21.83	11.60	4.85	f_3^1	9.1	10.2	0.2	0.2	8.9
f_3^2	0.26	0.26	19.13	7.65	6.81	f_3^2	16.1	15.7	0.2	0.4	4.0
f_3^3	0.69	0.32	15.17	1.56	0.27	f_3^3	6.7	7.5	3.8	3.9	3.9
f_3^4	23.61	18.40	0.43	5.30	12.42	f_3^4	0.7	0.7	12.3	9.5	1.3
f_3^5	18.76	10.16	0.83	0.98	0.97	f_3^5	5.7	5.6	9.1	9.0	4.7
f_3^6	18.10	7.63	0.61	1.56	1.16	f_3^6	0.9	1.3	13.0	13.0	7.1
f_3^7	22.26	24.13	0.46	9.19	17.56	f_3^7	0.6	0.6	9.0	10.0	2.2
f_3^8	8.85	0.21	23.37	10.73	5.32	f_3^8	4.8	6.3	4.2	0.2	3.4
f_3^9	0.92	0.95	19.31	1.03	0.88	f_3^9	6.5	6.5	5.3	7.2	6.0
f_3^{10}	0.45	0.31	19.19	1.30	0.57	f_3^{10}	4.6	4.3	5.7	1.1	6.3
f_3^{11}	0.40	0.31	17.99	10.42	0.51	f_3^{11}	8.5	8.7	2.0	0.5	2.3
f_3^{12}	4.53	16.60	0.23	0.38	1.79	f_3^{12}	0.2	0.2	1.8	8.5	0.8
f_3^{13}	14.33	20.46	0.22	1.32	8.89	f_3^{13}	0.6	0.4	7.8	11.5	4.9
f_3^{14}	13.11	17.82	0.19	1.20	10.84	f_3^{14}	0.3	0.3	8.6	13.3	6.6
f_3^{15}	7.95	17.10	0.26	0.39	3.55	f_3^{15}	6.3	5.8	4.6	5.5	4.9

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) in the case of 20 bins. As can be seen from the figure, the general characteristics of all four histograms are similar. Hence, the discriminant features within the class are preserved. Figure 7 shows the histogram distribution for another four different images of another person (class) in 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 supports the concept 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.

In order to justify the implementation of the method at the component level, we need to analyse the local statistical characteristics for a thermal image. Figure 10 shows a thermal image for one subject and the corresponding temperature distribution over the entire face. The temperature variations can be clearly seen over the different parts of the face. This shows that these parts have different thermal characteristics, giving the human face its own thermal identity. We take a further step in our analysis and show the thermal statistical features of the centre part of the face, f_3^i . The local distinctive features are obvious in Figure 11. Similar observation can be obtained when investigating the four thermal components $f_3^0, f_3^1, f_3^2, f_3^3$ shown in Figure 12. More distinctive features of thermal face components can be found in Figure 13 when we analyse the 16 components $f_3^0, f_3^1, f_3^2, f_3^3, f_3^4, f_3^5, f_3^6, f_3^7, f_3^8, f_3^9, f_3^{10}, f_3^{11}, f_3^{12}, f_3^{13}, f_3^{14}, f_3^{15}$. Figure 14 shows the histogram distribution for components $f_3^0, f_3^1, f_3^2, f_3^3, f_3^4, f_3^5, f_3^6, f_3^7, f_3^8, f_3^9, f_3^{10}, f_3^{11}, f_3^{12}, f_3^{13}, f_3^{14}, f_3^{15}$ corresponding to Figure

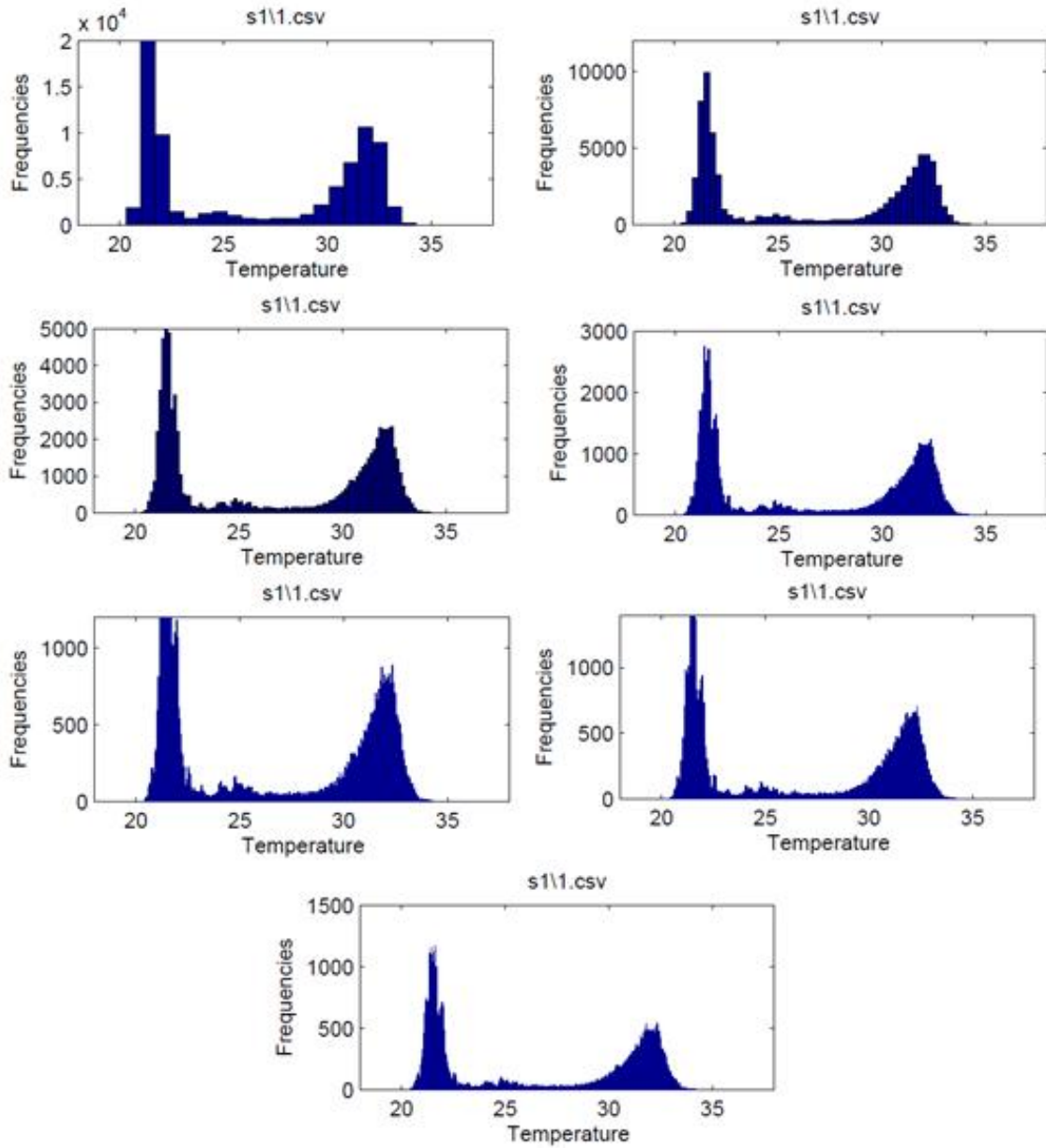
358 13(b). Figures 11 to 14 justify our rationale for using local thermal features for human
359 identification.

360 The recognition rates for the different number of bins are recorded in Figure 15. As can be
361 seen from the figure, the rank-1 recognition rate was at its lowest when the number of bins
362 was 20, with a success rate of 85.2%. The recognition rate increased as the number of bins
363 increased and reached 96.4% when there were 500 bins. We have noticed that the success
364 rate saturates as the number of bins becomes greater than 500. Another method to evaluate
365 the potential performance of the recognition system is the Cumulative Match Score curve
366 (CMS). The CMS illustrates the trade-off of true positive versus false positive results. The Y-
367 axis represents the true positive rate, and the X-axis is the cumulative rank. We can think of
368 the X-axis as the maximum number of images that the system is allowed to report when
369 giving an alarm for a given probe. If the system is allowed to report a larger number of
370 possible matches, the true positive rate generally increases. The results of the CMS
371 evaluation are shown in Figure 16, where the performance statistics are reported as
372 cumulative match scores. Identification is regarded as correct if the true object is in the top
373 Rank n matches, with Rank 1 being the best match.

374 For the sake of comparison, we show in Table 3 experimental results with thermal images. It
375 should be noted that the databases used by researchers in the mentioned works are not the
376 same. This is to be expected since this field of study is relatively new when compared to
377 face recognition in visible spectrum, and the community has not yet reached a general
378 agreement on standard tests or benchmark databases.

379 An important advantage of our system is its speed and efficiency. Table 4 shows the time
380 consumed by the system to complete the histograms of the different components. As can be
381 seen from Tables 3 and 4, the system performance demonstrates its effectiveness when
382 both the recognition rate and the time consumed are considered.

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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

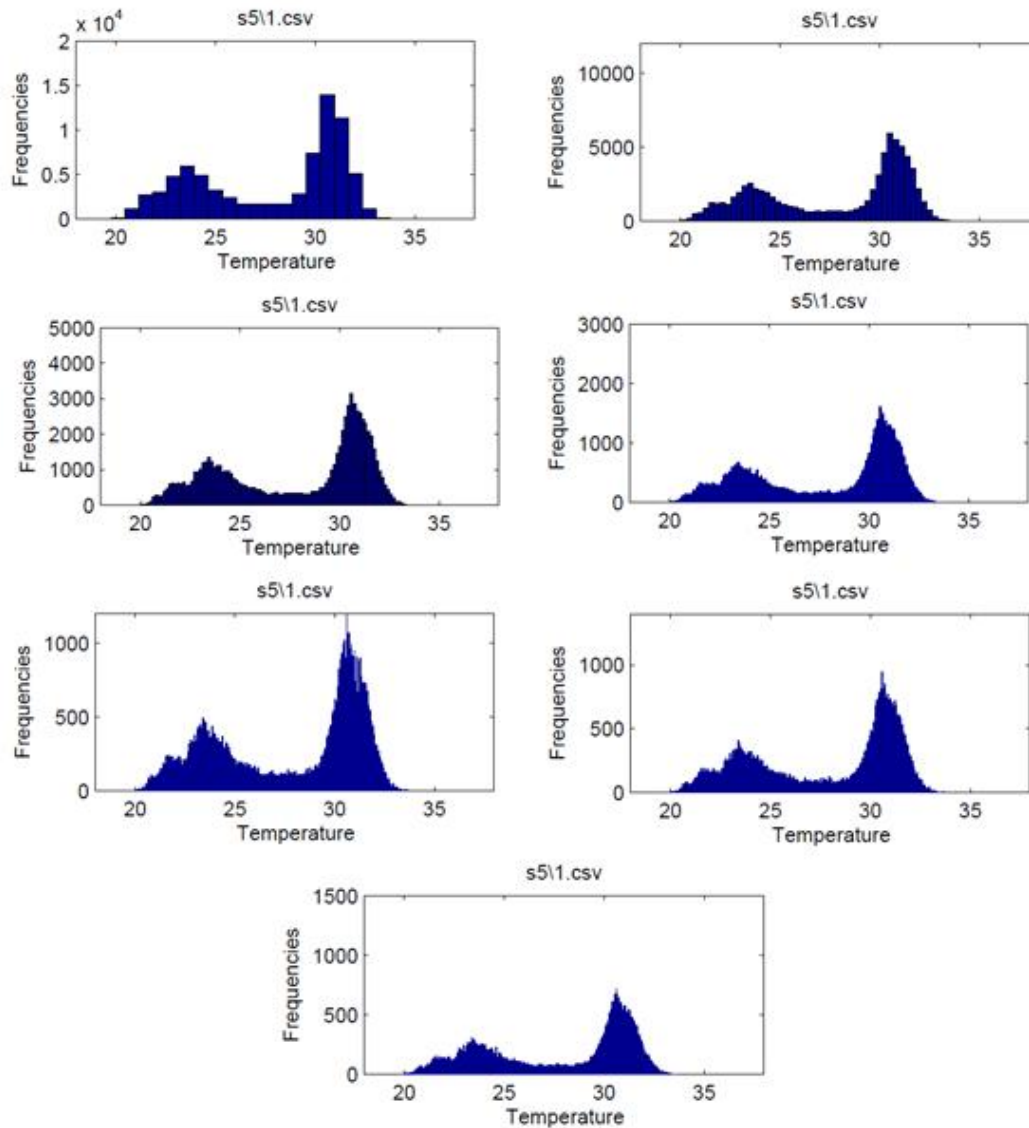


Figure 5. Histogram distribution for a whole face image for another subject (class) for the same number of bins as described in Figure 4

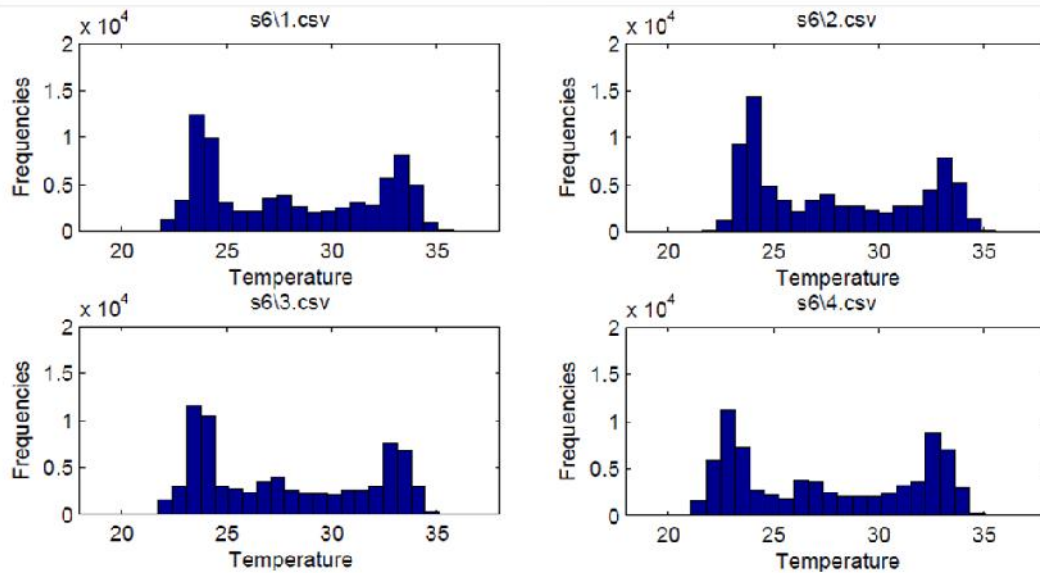


Figure 6. Histogram distribution for four different images for the same person (same class) in the case of 20 bins

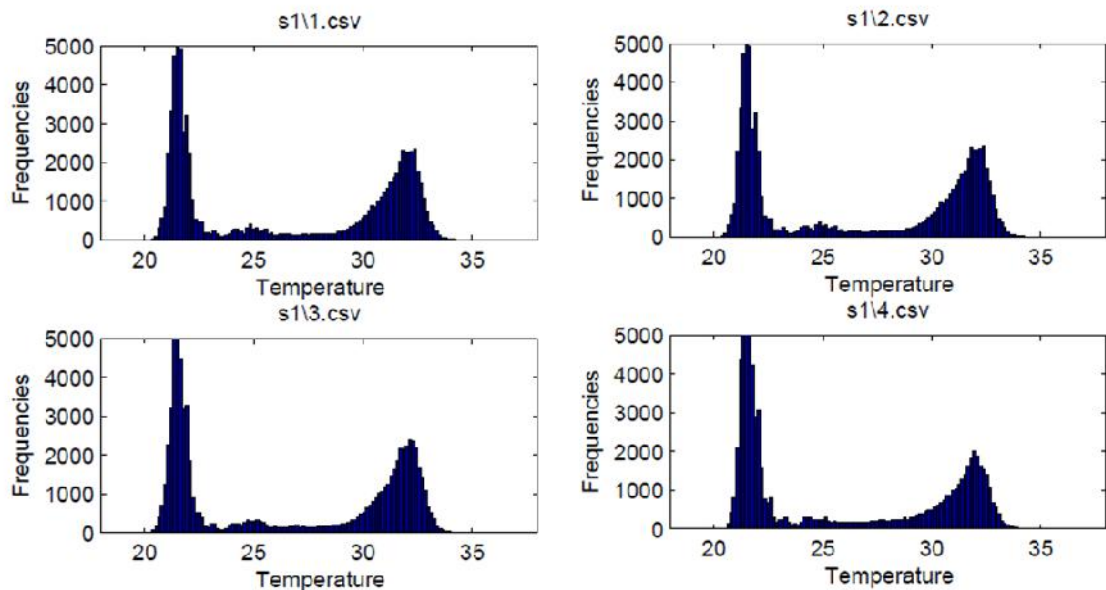
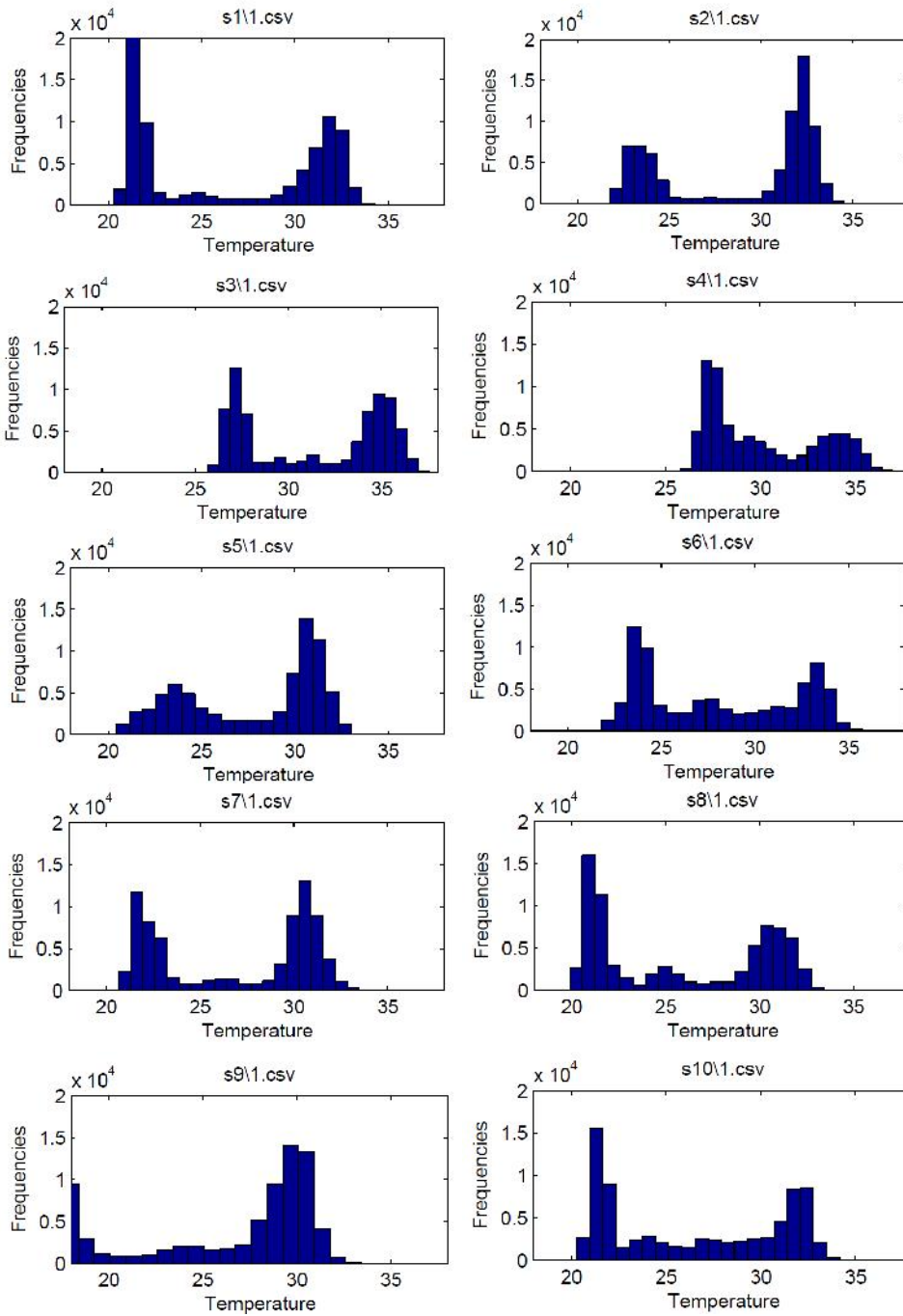


Figure 7. Histogram distribution for another four different images for another person (class) in the case of 100 bins

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

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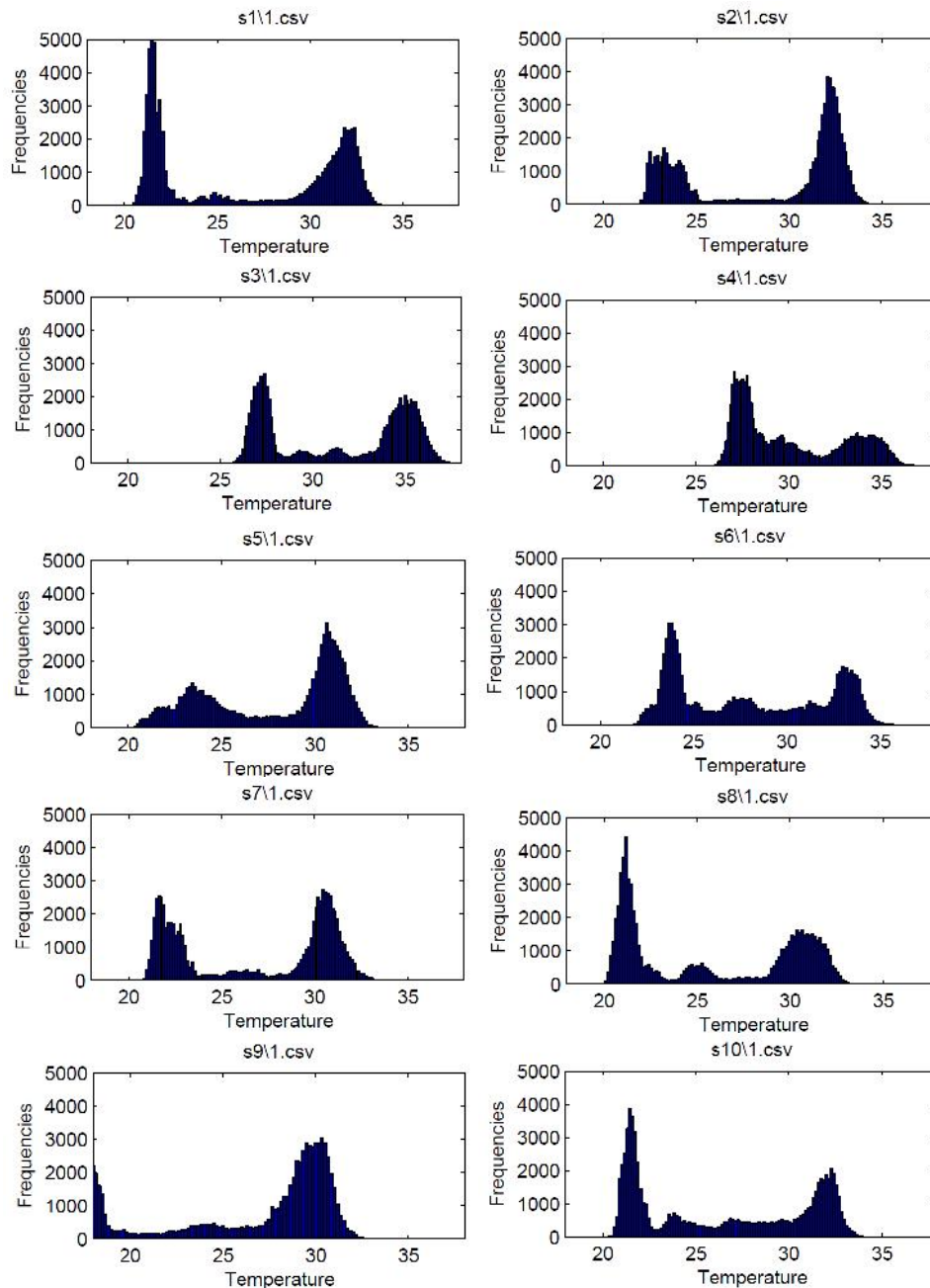


Figure 9. Histogram distribution for 10 different persons in the case of 100 bins

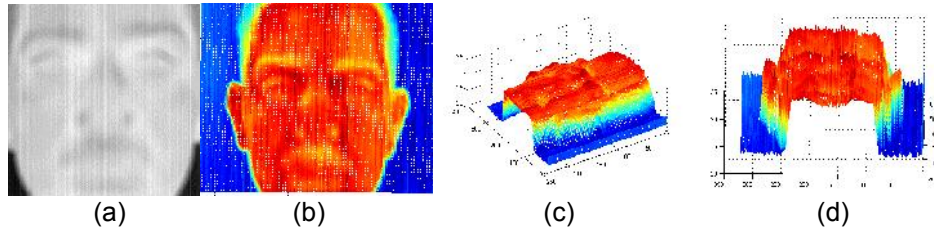


Figure 10. a) A thermal image corresponding to one person, b) A colour image showing temperature degree distribution of (a), c) 3D temperature distribution for (a), d) another 3D perspective for the same thermal face image

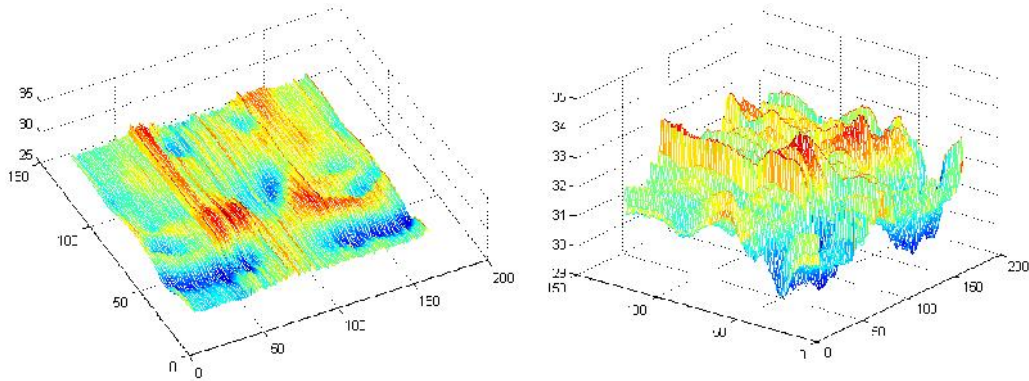


Figure 11. 3D temperature distribution from two angles corresponding to component f_1^0 for the person shown in Figure 10

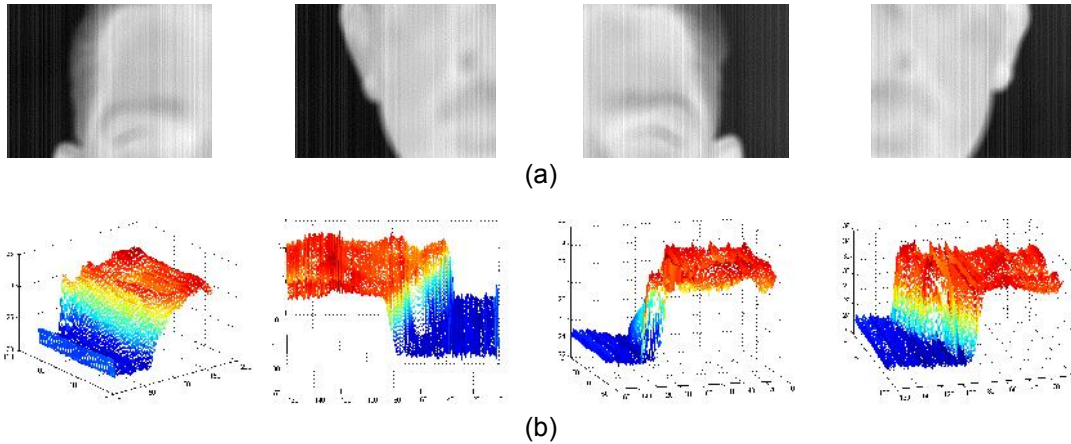


Figure 12. a) Four thermal image components $f_2^0, f_2^1, f_2^2, f_2^3$ corresponding to person shown in Figure 10, b) the corresponding 3D temperature distributions

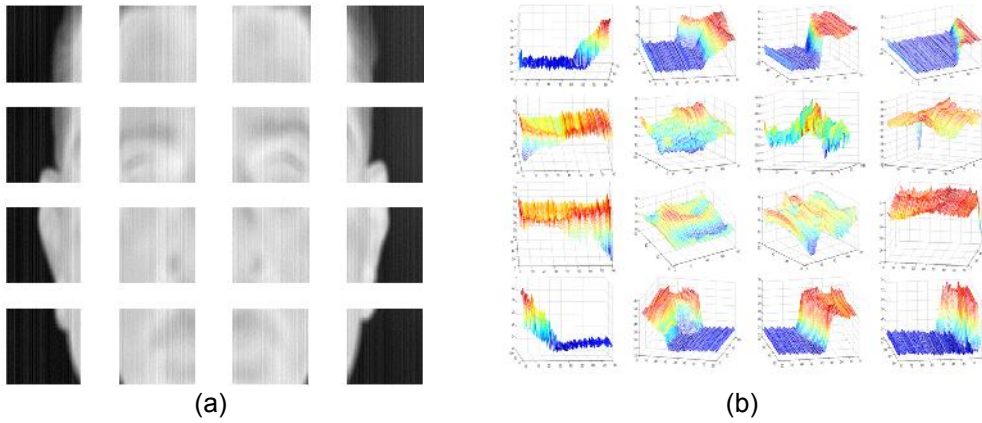


Figure 13. a) 16 thermal image components $f_2^0, f_2^1, f_2^2, \dots, f_2^{15}$ corresponding to person shown in Figure 10, b) the corresponding 3D temperature distributions

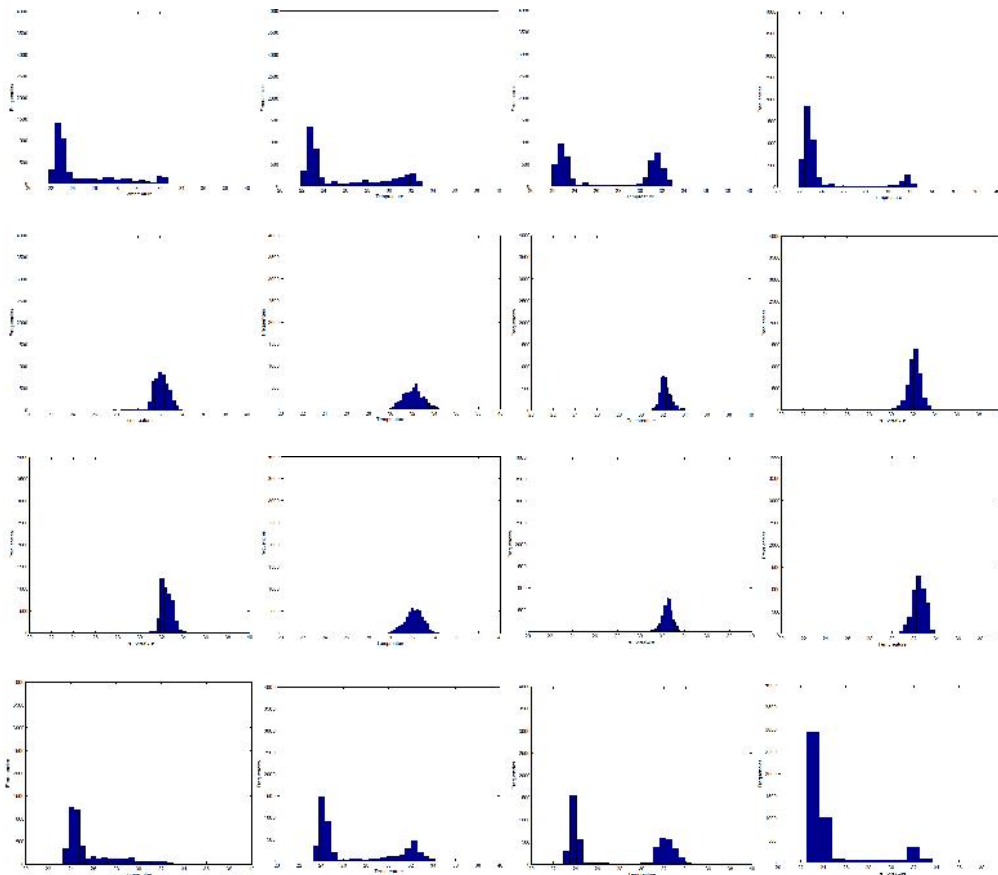


Figure 14. Histogram distribution for 16 different components $f_2^0, f_2^1, f_2^2, \dots, f_2^{15}$ corresponding to person shown in Figure 10

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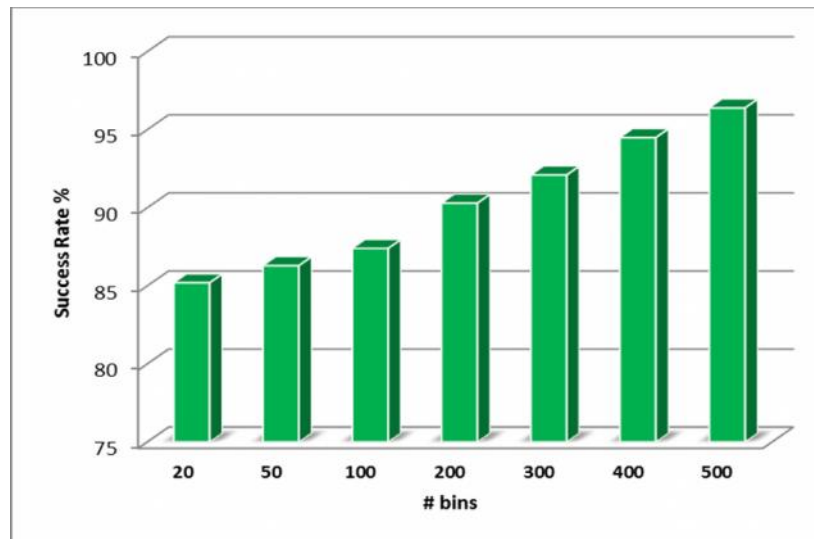


Figure 15. Recognition rates for different numbers of bins

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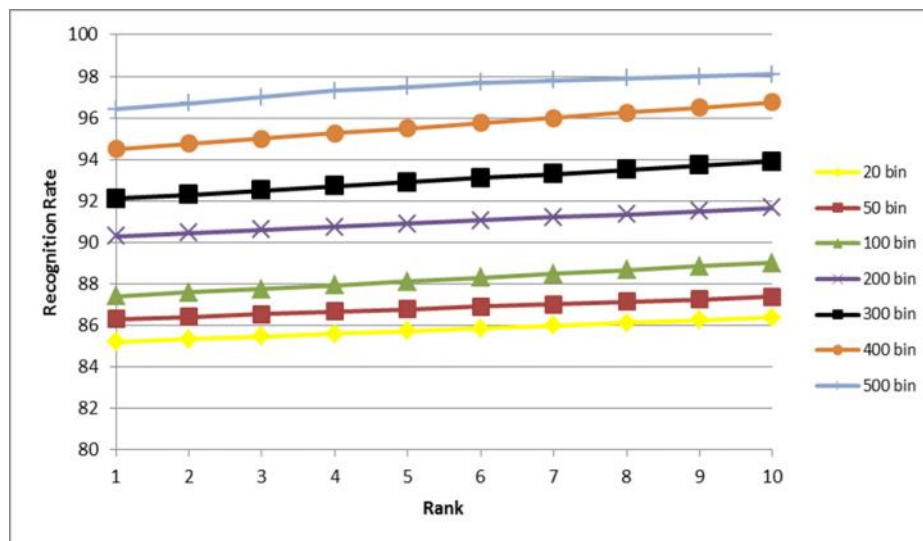


Figure 16. CMS evaluation results for different numbers of bins

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Table 3. Comparison between different thermal face recognition methods proposed in the literature

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Method	Success Rate (%)
Seal et al. [25]	95
Lu et al. [15]	89.1
Seal et al. [26]	97.6
Bhattacharjee et al. [27]	95.1
Hermosilla et al. [12]	95.7
Socolinsky et al. [10]	93.9
Bhowmik et al. [31]	93.8
Our method	96.4

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Table 4. Time consumed (in seconds) to calculate the histogram for each component in different images of the same subject

	Image 1	Image 2	Image 3	Image 4	Image 5
f_1^0	6.0E-03	6.1E-03	6.0E-03	6.0E-03	5.9E-03
f_2^0	6.2E-03	5.9E-03	6.0E-03	5.9E-03	5.9E-03
f_2^1	5.9E-03	5.9E-03	5.9E-03	6.3E-03	5.9E-03
f_2^2	5.9E-03	5.9E-03	5.9E-03	5.9E-03	6.1E-03
f_2^3	6.0E-03	5.9E-03	6.7E-03	5.9E-03	5.9E-03
f_3^0	5.6E-03	5.6E-03	5.6E-03	5.6E-03	5.6E-03
f_3^1	5.6E-03	5.5E-03	5.6E-03	5.7E-03	5.6E-03
f_3^2	5.6E-03	5.6E-03	5.6E-03	5.6E-03	5.5E-03
f_3^3	5.6E-03	5.6E-03	5.6E-03	5.8E-03	5.6E-03
f_3^4	5.5E-03	5.6E-03	5.6E-03	5.8E-03	5.6E-03
f_3^5	5.6E-03	5.7E-03	5.6E-03	5.6E-03	5.6E-03
f_3^6	5.6E-03	5.6E-03	5.7E-03	5.7E-03	5.7E-03
f_3^7	5.6F-03	5.6F-03	5.6F-03	5.6F-03	5.6F-03
f_3^8	5.6F-03	5.6F-03	5.6F-03	5.6F-03	5.6F-03
f_3^9	5.6F-03	5.6F-03	5.6F-03	5.6F-03	5.7F-03
f_3^{10}	5.6F-03	5.6F-03	5.6F-03	5.7F-03	5.6F-03
f_3^{11}	5.6E-03	5.6E-03	5.6E-03	5.6E-03	5.9E-03
f_3^{12}	5.6E-03	5.6E-03	5.9E-03	5.5E-03	5.7E-03
f_3^{13}	5.6E-03	5.6E-03	5.6E-03	5.6E-03	5.7E-03
f_3^{14}	5.7E-03	5.6E-03	5.6E-03	5.6E-03	5.6E-03
f_3^{15}	5.5E-03	5.6E-03	5.5E-03	5.5E-03	5.8E-03

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6. CONCLUSION

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