Thermal Face Recognition Using Moments Invariants

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***Abstract*—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 new technique for face recognition based on statistical calculations of thermal images. We propose the use of moments invariants which become one of the most important shape descriptors. The proposed feature vector consists of 11 different moments, where three of them are geometric moments and the rest eight are central geometric moments that offer robustness against variability due to changes in localized regions of the faces. The new method has been tested on a new database comprising of images of different expressions, different lightings, and were taken within different time-lapse. The work is reinforced by a discussion of body and face physiology behind thermal face recognition.**

***Index Terms*—face recognition, thermal image, feature extraction, moments invariants**

I. Introduction

The attempts to recognize and identify humans using machines go back three decades, when computers began to impact on our lives. Researchers found that it is important to attempt to understand the strategies that the biological system employs, as a first step towards eventually translating these strategies into machine-based algorithms. These observations provide useful hints that can be valuable to computer vision systems [1]. Accurate automatic personal identification is now needed in a wide range of civilian applications involving the use of passports, cellular telephones, automatic teller machines, and driver licenses. In our electronically inter-connected society, reliable and user-friendly recognition and verification system is essential in many sectors of our life. In this regard, the person's physiological or behavioral characteristics (known as biometrics) are important and vital method for identification and verification.

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. Face recognition, being straightforward, passive and non-invasive comparing with other biometrics, has a nature place in biometric technology and computer vision. Currently, most researches on face recognition focus on visual images. Although considerable progress has been made in the domain of face recognition over the last decade, especially with the development of powerful methods, face recognition has shown to be not accurate enough in uncontrolled environments. Face recognition performances of a system can be degraded by many factors, including facial expression, head pose variation, occlusion and most importantly illumination changes. Face recognition based only on the visible spectrum has shown difficulties in performing consistently in uncontrolled operating conditions [2].

Face recognition using different imaging modalities, particularly infrared (IR) imaging sensors, has become an area of growing interest [3]. Over the last few years, thermal IR imaging based face recognition has emerged as a promising complement to conventional visible spectrum based approaches which continue to struggle when applied in practice. In an effort to overcome some of the key challenges, such as appearance changes due to varying illumination and disguises (including facial wear and hair), the use of imaging outside the visible part of the electromagnetic spectrum (wavelength approximately in the range 390-750nm) has been explored. Different objects emit different range of infrared energy according to their temperature and characteristics. The range of human face and body temperature is nearly the same and quite uniform. This provides a consistent thermal signature. The thermal patterns of faces are derived primarily from the pattern of superficial blood vessels under the skin. The vein and tissue structure of the face is unique for each person and, therefore, the IR images are also unique.

In this paper, we present a new technique for face recognition that exploits the statistical characteristics of a thermal image by the virtue of moments invariants. The statistical features of the images find a combination of multiple statistical patterns to produce a result that is

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enhanced in terms of information content for pattern recognition and classification. Moments invariants offer robustness against variability due to the changes in regions of the objects. The features used in moments analysis are less sensitive to illumination changes, easier for estimating the rotations and have less computational burden. Our work proposes a way to achieve thermal face image representation in a simple manner. The evaluation used a database of thermal face images that has been recently developed in the Artificial Intelligence laboratory at the Arab Open University (AIAOU Database) [4]. The organization of the paper is as follows. A brief literature review is given in Section 2. Section 3 presents a physiology perspective behind thermal face recognition. A mathematical background of the proposed method is furnished in Section 4. The experimental results are discussed in Section 5. Finally, the paper is brought to a conclusion 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 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 [5]. 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 [6], [7] 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.* [8] 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.

Oz and Khan [9] found that variances in thermal intensity values recorded at facial thermal feature points can help classify intentional facial expression by using multivariate tests and linear discriminant analysis. Bhowmik, *et al.* [10] introduced the role of different IR spectrums and their applications. In their experimental work, they fused both thermal and visible images to enhance the recognition rate, as it is expected that the fusion process improves the overall performance of the system. They tested their method on IRIS and Terravic databases. The images of both databases were taken in one session. In other words, the effect of time lapse was not taken into consideration. Jiang, *et al.* [11] conducted the facial expression recognition through drawing and analyzing the geometry characteristics in infrared images by using mathematics morphology. He, *et al.* [12] proposed using the Deep Boltzmann Machines (DBM) for facial expression recognition. First, the face is located and normalized. Then, a DBM model, which consists of two layers of Restricted Boltzmann Machine (RBM), is applied. A DBM is a multilayer generative network with several neurons in each layer. Guzman, *et al.* [13] 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. Buyssens and Revenu [14] addressed how to fuse the visible and infrared modalities. Three different levels of fusion have been considered, an image-based level, a feature-based level and a score level. Their study and comparison was demonstrated using eigenfaces algorithm and sparse approach. However, in their study they have presented the identification rates on a database taken from the same session.

III. Physiology Perspective

Human beings are motivated to interact with the environment in such a way to keep the bodies within a narrow range of temperatures. The need for such regulation is that the cells of the body are fine-tuned for a constant temperature, and deviations from this temperature interfere with cellular functions [15]. As such, body temperature is typically affected by activity, eating, and time of day. Neurons that change their firing rate in response to small changes in temperature are found throughout the brain and spinal cord. The most important neurons for temperature homeostasis, however, are found clustered in the anterior hypothalamus, which sends axons all the way to the lateral horn of the spinal cord. These cells transduce small changes in blood temperature into changes in their firing rate [16]. The hypothalamus contains thermosensitive neurons which initiate appropriate responses to changes in the core temperature of the body. Activity of these neurons is reinforced by thermal information received from thermosensitive neurons supplying the skin. A slight change in the core temperature can usually be corrected by directing blood flow into or away from the skin, as appropriate [17]. A demonstration of principal extracranial branches of the facial nerve is shown in Fig. 1.

Thousands of chemical reactions occur each instant throughout the body; this coordinated process of chemical change is termed metabolism. Metabolism includes the synthesis and breakdown of organic molecules required for cell structure and function and the release of chemical energy used for cell functions. Chemical reactions involve (1) the breaking of chemical bonds in reactant molecules, followed by (2) the making of new chemical bonds to form the product molecules. Since the energy contents of the reactants and products are usually different, and because energy can neither be created nor destroyed, energy must either be added or released during most chemical reactions [16]. The energy that is released appears as heat, which is measured in units of calories. One calorie is the amount of heat required to raise the temperature of 1g of water 1 °on the Celsius scale. Although very little is known about the structure of thermoreceptive nerve endings, physiologists and neuroscientists do know that temperature sensitivity is not spread uniformly across the skin. At room temperature, skin arterioles are already under the influence of a moderate rate of sympathetic discharge. An appropriate stimulus-cold, fear, or loss of blood, for example, causes reflex enhancement of this sympathetic discharge, and the arterioles constrict further. In contrast, an increased body temperature reflexly inhibits the sympathetic nerves to the skin, the arterioles dilate, and the skin flushes as body heat is radiated [17]. Also, the intensity of the emitted energy from an object varies with temperature and radiation wavelength. In addition to emitting radiation, an object reacts to incident radiation from its surroundings by absorbing and reflecting a portion of it, or allowing some of it to pass through.

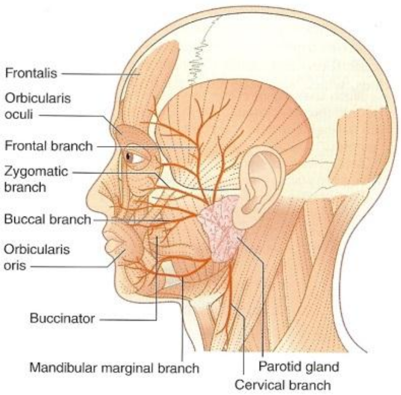


Figure 1. Principal extracranial branches of the facial nerve [16].

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. In the literature, it has been customary to divide the IR spectrum into four sub-bands: near IR (NIR; wavelength 0.75-1.4 µm), short wave IR (SWIR; wavelength 1.4-3 µm), medium wave IR (MWIR; wavelength 3-8 µm), and long wave IR (LWIR; wavelength 8-14 µm). This division of the IR spectrum is also observed in the manufacturing of IR cameras, which are often made with sensors that respond to electromagnetic radiation constrained to a particular sub-band. One of the largest differences between different IR sub-bands emerges as a consequence of the human body’s heat emission spectrum. Specifically, most of the heat energy is emitted in LWIR sub-band, which is why it is often referred to as the thermal sub-band. Significant heat is also emitted in the MWIR sub-band. Both of these sub-bands can be used to passively sense facial thermal emissions without an external source of light. Motivated by the abovementioned discussion, we propose a new face recognition system that exploits the advantages and the characteristics of thermal images and statistical features.

IV. THEORY OF MOMENTS INVARIANTS

The approach using invariant features appears to be the most promising and has been used extensively. Its basic idea is to describe the objects by a set of measurable quantities called invariants that are insensitive to particular deformations and that provide enough discrimination power to distinguish objects belonging to different classes [18]. From a mathematical point of view, invariant I is a functional defined on the space of all admissible image functions that does not change its value under degradation operator D, i.e. that satisfies the condition $I(f) = I(D(f))$ for any image function f. This property is called invariance. Another desirable property of I, as important as invariance, is discriminability. For objects belonging to different classes, I must have significantly different values. Usually, one invariant does not provide enough discrimination power and several invariants $I_1, \ldots, I_n$ must be used simultaneously. This will lead to having an invariant vector. In this way, each object is represented by an-dimensional vector space called feature space or invariant space. Moments are scalar quantities used to characterize a function and to capture its significant features. From the mathematical point of view, moments are “projections” of a function onto a polynomial basis. Depending on the polynomial basis used, various systems of moments can be recognized. Moment invariants have become one of the most important and most frequently used shape descriptors. Despite a tremendous effort and a huge number of published papers, many problems remain to be resolved. In this paper, we propose using moments invariants for thermal face recognition. The mathematical basis of the proposed method is described below.

If the image can have nonzero values only in the finite part of xy-plane, then moments exist. Geometric moment of order $(p+q)$ for a two dimensional discrete function is computed using (1),

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

where $f(x, y)$ is the image function and M, N are image dimensions. Geometric moments of low orders have an intuitive meaning – m_{00} is a “mass” of the image, m_{10}/m_{00} and m_{01}/m_{00} define the *center of gravity* or *centroid* of the image. Second-order moments m_{20} and m_{02} describe the “distribution of mass” of the image with respect to the coordinate axes. Characterization of the image by means of geometric moments is complete in the following sense. For any image function, geometric moments of all orders do exist and are finite. The image function can be exactly reconstructed from the set of its moments. Invariance to translation can be achieved simply by seemingly shifting the object such that its centroid coincides with the origin of the coordinate system or, vice versa, by shifting the polynomial basis into the object centroid. In the case of geometric moments, we have the so-called *central* geometric moments

$$\mu_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^p (y-\bar{y})^q f(x,y) \quad (2)$$

where $f(x, y)$ is the image function and M, N are image dimensions, and $\bar{x} = m_{10}/m_{00}$, $\bar{y} = m_{01}/m_{00}$ are the coordinates of the object centroid. In this work, we propose a feature vector I consisting of 11 different moments where three of them are geometric moments and the rest are eight central geometric moments, given by the following

$$I = [m_{00}, m_{10}, m_{01}, \mu_{11}, \mu_{12}, \mu_{21}, \mu_{22}, \mu_{30}, \mu_{03}, \mu_{40}, \mu_{04}] \quad (3)$$

where

$$m_{00} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \quad (4)$$

$$m_{10} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x f(x,y) \quad (5)$$

$$m_{01} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} y f(x,y) \quad (6)$$

$$\mu_{11} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x}) \quad (y-\bar{y}) \quad f(x,y) \quad (7)$$

$$\mu_{12} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x}) \quad (y-\bar{y})^2 f(x,y) \quad (8)$$

$$\mu_{21} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^2 (y-\bar{y}) \quad \mathrm{f}(x,y) \quad (9)$$

$$\mu_{22} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^2 (y-\bar{y})^2 f(x,y) \quad (10)$$

$$\mu_{30} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^3 f(x,y) \quad (11)$$

$$\mu_{03} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (y-\bar{y})^3 f(x,y) \quad (12)$$

$$\mu_{40} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (x-\bar{x})^4 f(x,y) \quad (13)$$

$$\mu_{04} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (y-\bar{y})^4 f(x,y) \quad (14)$$

The choice of the elements of this vector is based on exploiting the characteristics of every corresponding moment. The Euclidean distance (L_2 norm) is used as the system classifier and is given by

$$D(\boldsymbol{a},\boldsymbol{b}) = \left(\sum_{k=1}^{d} (a_k - b_k)^2 \right)^{1/2} \quad (15)$$

for vectors **a** and **b** both of *d* dimensions.

V. Experimental Work

We have built a database consisting of 1500 images for 20 different subjects taken in different sessions. The images are of varying poses, expression, and lighting conditions [4]. Acquisitions were held at different times across a number of different weeks. Further, the database consists of males and females from various ethnic backgrounds. We used the Infrared Camera ETIP 7320 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 high efficient thermal and spatial resolution. In this work we demonstrate the effectiveness of our method on part of the database comprising of frontal images under different expressions and lighting conditions. Examples of thermal images from the AIAOU database for one subject are shown in Fig. 2. Fig. 3 shows a thermal image corresponding to one subject with 3D temperature degree distribution. Each face recognition experiment is characterized by three image sets: a) The training set: used to form a face space in which the recognition is performed. b) The gallery set: contains the set of "enrolled" images of the subjects to be recognized, and each image is uniquely associated with the identification of a distinct subject in the set. c) The probe (testing) set: is a set of images to be identified via matching against the gallery. Before conducting our experiments, we took several pre-processing steps:

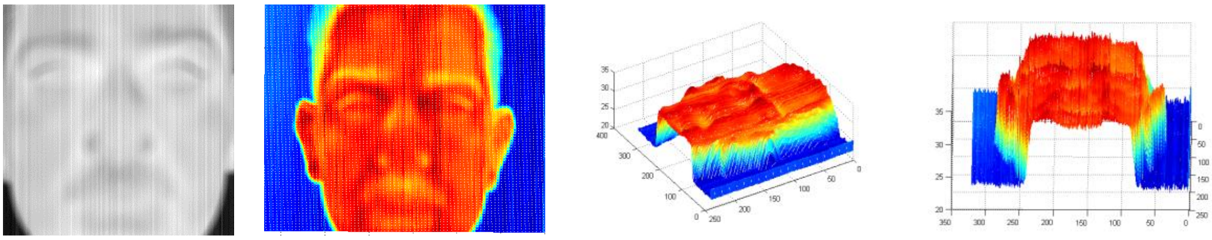
a) Integer to float conversion: After the image is read from a file, it is converted to double precision floating point for subsequent image calculations.
b) Geometric normalization: This aligns images such that the faces are the same size.
c) Masking: This is used to eliminate less important parts of the image, ensuring that the facerecognition system does not respond to features corresponding to background, hair, clothing, etc.

TABLE I. Comparison between Different Thermal Face Recognition Methods

Method	Success rate (%)
Lu, *et al.* [19]	89.1
Seal, *et al.* [20]	97.6
Bhattacharjee, *et al.* [21]	95.1
Socolinsky, *et al.* [7]	93.9
Bhowmik, *et al.* [10]	93.8
Our method	97.5

Table I shows the recognition rates obtained by the proposed method, as well as the experimental results obtained by different researchers. It should be noted that the databases used by researchers in the mentioned works are not the same. This is to be expected since this field of study is relatively new when compared to face recognition in visible spectrum, and the community has not yet reached a general agreement on standard tests or benchmark databases.

Figure 2. Examples of thermal images from the AIAOU database for one subject: frontal view with different expressions and different lighting conditions.



(a) (b) (c) (d)

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

VI. CONCLUSION

Face recognition using infrared imaging sensors can improve the performance of face recognition in uncontrolled illumination conditions. In this paper, we presented a new technique for face recognition based on statistical calculations of thermal images. We proposed the use of moments invariants which become one of the most important shape descriptors. Our proposed feature vector consists of 11 different moments, where three of them are geometric moments and the rest eight are central geometric moments that can offer robustness against variability due to changes in localized regions of the faces. The new method has been tested on a new database comprising of images of different expressions, different lighting conditions, and were taken within different time-lapse. The experimental work achieved rank-1 recognition rate of 97.5%. Our future work will consider implementing the method on different poses and other benchmark databases.

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