An Overview of Thermal Face Recognition Methods

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***Abstract* – The popularity of surveillance systems grows as well as a need for better security systems particularly in a bad lighting conditions or at night. The aim of a security system is to collect as many details as possible to enable a better recognition of persons. In this paper, a comparison of representative thermal face recognition methods will be given, emphasizing their strengths and weaknesses. Then, trends in the development of surveillance and security systems will be outlined such as fusion of visible and thermal images and use of convolutional neural networks. Also, existing challenges of thermal facial recognition and its applications in a real world will be pointed out.**

Keywords: thermal facial biometrics, thermal imaging, face recognition, surveillance, access control

I. Introduction

Video surveillance systems are placed everywhere, and a need for a better security system is growing. Today, cameras monitor banks, airports, schools, important or popular places where people gather or hang out, border crossings and all protected areas and infrastructure objects.

The video surveillance industry is not new but has significantly changed in last 20 years when high-quality digital cameras and network-based video surveillance systems were used [1]. Earlier video surveillance systems were very dependent on human operator who had to monitor the video footages of protected areas and detect a presence of persons in the monitored area. Also, the operator should recognize each authorized person and accordingly approve or reject access. Later on, surveillance systems are associated with biometric systems that took the role of recognizing authorized/ unauthorized persons and of access permission [2].

Most biometric systems use standard video cameras that capture face or palm images in the visual part of the spectrum [3]. However, because of an increasing demand for a better security systems and for a better surveillance in night-time and poorly illuminated areas, the thermal cameras are nowadays included into the system, Fig.1.

Fig. 1 Application of thermal cameras in real-world applications [4]

The thermal infrared (IR) camera captures the heat emitted by the subject of the surveillance and forms an image using IR radiation, so-called thermogram. In surveillance systems these images are used for object detection (e.g. ability to distinguish an object from the background), recognition (e.g. ability to classify an object in one of the classes like human, animal, vehicle) and ability to describe monitored object in details (like a man with a coat, a woman with a hat, a bear, …). It is a non-intrusive way of identifying a person since the camera can capture face from certain distances away. The identification or verification of people based only on their thermal information is not an easy task to accomplish, but thermal face biometrics can contribute to that task.

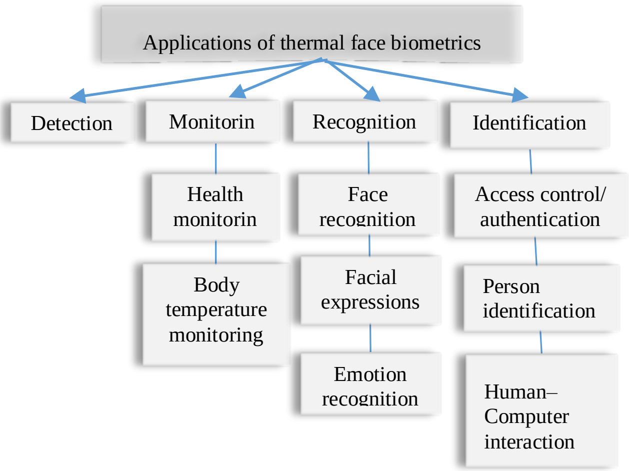


Fig. 2 Thermal biometrics applications

Application areas of thermal face biometrics are broad including identification and access control to secure computer networks and facilities such as government buildings, authentication for secure banking and financial transactions, automatic screening at airports for known terrorists, and video surveillance usage, recognition of face expression for high-end security applications, monitoring body temperature for medical diagnostics, etc., Fig. 2. Due to the omnipresence of surveillance cameras, there is a concern about privacy protection, so de-identification methods are developed in parallel [6].

In this paper, an overview of thermal facial features and methods that have proven to be successful in detection and person recognition and verification will be given. In Section II characteristic of infrared images are highlighted. Kinds of features commonly extracted from facial thermal images and comparison of thermal recognition methods are given in Section III. In Section

IV. commonly used datasets in terms of IR band usage and application purposes are listed. Research trends such as use of CNN, and fusion of visible and thermal images as well as remaining challenges in facial thermal biometrics and its applications in real-world applications are pointed out in Discussion and Conclusion.

II. Infrared Thermal Imaging Basics

Infrared (IR) thermal sensors have the capability of imaging scenes and objects based upon either the IR light reflectance or upon the IR radiation emittance. The IR radiation is an electromagnetic radiation emitted in proportion to the heat generated/ reflected by an object and, therefore IR imaging is referred to as thermal imaging. The wavelengths of IR are longer than those of visible light, so IR is invisible to humans [6].

The IR spectrum can be divided given the wavelength (Fig. 3) in the following bands according to [7]:

- Near-Infrared - NIR, ranges from 0,7 to 1 µm;
- Short-Wave infrared - SWIR, ranges from 1 to 3 µm;
- Mid-Wave infrared - MWIR, ranges of 3 to 5 µm;
- Long-Wave infrared - LWIR, ranges from 8 to 14 µm;
- Very Long-Wave infrared - VLWIR, in a range greater than 14 µm.

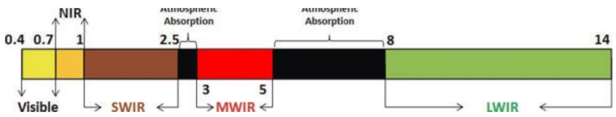


Fig. 3 Electromagnetic spectrum with illustrated IR segments wavelengths in µm [7]

The NIR and SWIR bands are sometimes referred to as "the reflected infrared radiation" and MWIR and LWIR bands as "thermal infrared radiation". The latter does not require an additional source of light or heat since the thermal radiation sensors can form an image of the environment or object solely by reading the emission of thermal energy of observed objects in the scene, Fig. 4. Since IR sensors depend on the amount of emission of the thermal energy of a recorded object, they are, unlike the visible light cameras, invariant to illuminating conditions, robust to a wide range of light variations [4, 8] and weather conditions, and so can operate in a total darkness.

Fig. 4 Thermal vs. visual image (www.multicopterwarehouse.com)

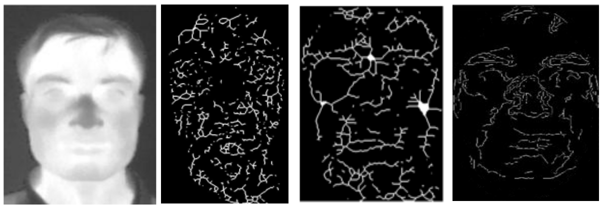
On the other hand, IR cameras are very sensitive to the variations of surrounding's temperature and provide fewer details than visible light cameras since color captured in visible spectrum provides much more information and is easier to interpret.

Thermal face images can be captured under SWIR, MWIR and LWIR bands. Differences between the face image in the visual and IR bands are presented in Fig. 5. Lighter areas are with higher temperature (eyes, lips) and it is obvious that level of detail on face image decreases with the wavelength increase, that is, the most details are in the image captured with the visual camera, and the least with the LWIR cameras. To achieve full invariance to lighting conditions, the LWIR band is mostly used [4, 8].

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

Fig. 5 A face simultaneously imaged in the (a) visible spectrum, 0.4 - 0.7 µm; (b) short-wave infrared, 1,0 – 3,0 µm; (c) mid-wave infrared, 3,0 – 5,0 µm; (d) long-wave infrared, 8,0-14,0 µm [8].

Furthermore, when IR images are captured in high resolution, the anatomical information, such as the structure of the blood vessels and the tissue on the face can be extracted from IR imaging (Fig. 6).



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

Fig. 6 Face grayscale thermal image (a), blood perfusion obtained transforming a medial axis on bit-plane (b); morphological gray level erosion and medical axis transform (c); result of Sobel operator (d) [9]

Due to the difference between visual and thermal images, the features and traditional methods for face recognition had to be tailored to properties of thermal images in order to achieve better recognition performance.

III. Thermal Face Recognition Methods

The human face is a biometric feature that can be used in security systems for person identification or authentication. The main challenge of the face recognition methods is to accurately match the input face with the face image of the same person already stored in the system database. In case of thermal face recognition, methods deal with facial thermograms. A related task and a prerequisite for face recognition is the detection of a face in the image. For the purposes of thermal face recognition, a thermal face image should be represented with biometrics features that highlight thermal face characteristic and are compact and easy to use for classification. Since thermal face images provide different details than images in visible spectrum it was necessary to define features that can be used in thermal biometrics.

Recently, a comprehensive survey on thermal face recognition methods has been published [10]. The authors analyze the influence of local and global descriptors on recognition performance. Some of the used descriptors were Local Binary Pattern (LBP) [11], the WLD (Weber

Linear Descriptor) [12], the GJD (Gabor Jet Descriptor) [13], SIFT (Scale-Invariant Feature Transform) [14] and SURF (Speeded Up Robust Features) [15] and the best results were reported with SIFT descriptor. In [16] a wide range of methods for facial recognition on the thermal images are presented and grouped as: Appearance-Based Methods, Feature-Based Methods, Multi-Spectral and Hyper-Spectral Methods, Multimodal Methods and other Approaches based on geometric invariant moments [17], elastic graph matching [18], isotherms [19], and other methods [20-22]. In [23] the authors give an overview of different approaches for the face recognition using fusion of thermal and visible images, heterogeneous face recognition using concatenated features, as well as application of deep neural networks for the thermal face recognition.

Here, general approaches to thermal face recognition are pointed out, with their strengths and weaknesses. Representative recognition methods are compared and difference highlighted in terms of IR band, environment conditions, features, datasets, application of recognition methods and performance.

Problems of intra-spectral and cross-spectral face recognition in different environments are presented in [7, 23]. The authors have tested the performance of face recognition in different IR bands vs. visible face images as well as between different IR bands when conditions of environment and distance change. The authors have demonstrated the feasibility of intra-spectral and cross-spectral matching, e.g. a 100% accuracy was achieved with visible vs. SWIR band under controlled conditions at a distance of 30 m. They also showed that with increasing recording distance, the recognition rate decreases regardless of IR band used, especially when the distance is greater than 90 m.

In [24], experiments were conducted on the multispectral images from the Equinox multimodal facial image dataset (Visible, SWIR, MWIR, LWIR) [25] and Laval University Multispectral Database (Visible, NIR, MWIR, LWIR), developed by the authors. The face images contain variations like facial expressions, pose, eyeglasses, beard, etc. To reduce sensitivity to noise, illumination conditions and facial expressions, texture features are extracted from thermal images. Face regions are represented by local binary descriptors (LBP) and local ternary descriptors (LTP), and simple differential LTP (DLTP).

Authors have reported the best accuracy (96%) on SWIR images from Equinox dataset when a combination of LBP descriptors and LLE methods for dimensionality reduction is used. The Laval University Multispectral Database better shows real conditions, so the best result (86%) are achieved with LBP in MWIR band. Reported results have shown that texture descriptors are a good solution for multispectral face recognition system, particularly in case of illumination changes and facial expression variations.

The effectiveness of LBP descriptors for face recognition purpose on LWIR images from Equinox dataset was presented in [26]. LWIR images are insensitive to the illumination conditions but are sensitive to the noise. Several scenarios were tested in experiment e.g. the presence of glasses, different facial expressions, etc. A satisfactory recognition rate of 97,3% was reported even with a presence of glasses, and without image pre-processing. A Bayesian probabilistic framework and SVM are used for the thermal face detection and identification in [27]. The experiment was conducted on images from Equinox and Laval University multispectral face databases. The best-reported result was 95% obtained with LDA method in LWIR band.

In [28] images were collected recording 24 persons with two facial expressions (normal, smile) at a distance of approx. 2m and from three viewpoints (frontal, 45°, profile), giving a total of 288 images. Experiments were conducted applying Eigenfaces and have reported 96% of identification accuracy for frontal face and 100% for profile images.

Approach for human face recognition that uses veins structure in thermal face image is proposed [29]. The topology of the vascular network depends on the genetic and physical characteristics of each person (e.g. face skin, fat deposits). To be used as a biometric feature, a facial vascular network should be segmented first using common segmentation methods such as region growing or directional anisotropic diffusion (DAD). In [29] authors stated that facial veins structure provides a unique thermal face signature similar to a fingerprint. For classification, a five-layer feed-forward back propagation neural network has been used, and the highest recognition accuracy of 95,24% was achieved when bit-plane slicing and medial axis transform were used for extraction of vein structure. The main advantage of this approach is a simple implementation, independent of face geometry. The disadvantage is that the face should be taken at short distances and with a uniform background.

Regions of the thermal image with heat imbalance present a physiological information. A heat imbalance arises as a result of the convection heat effect of blood flow in the main face surface vessels. The human face temperature is uniform and ranges from 35.5°C to 37.5°C in healthy people, providing a consistent thermal signature unique for each person. A thermal face pattern can be obtained with segmentation and morphological operations (e.g. dilatation, erosion, reconstruct, …).

In [29] a body heat transfers and Penn's equation [30] were proposed to improve the performance of IR face recognition. Application of Penn's equation converts the thermal information into blood perfusion rate, which is a discriminative facial biological feature of the face image. Similarly, in [31] a face recognition system RIFARS was proposed. Reported recognition accuracy was up to 98% and one of the key reason for high performance was the robustness to variable ambient temperatures.

The authors in [32] stated that face recognition on thermal images should focus on changes in temperature on facial blood veins. Furthermore, they pointed out that these temperature changes can be observed as texture features and have proposed Haar wavelet transform for extracting the low-frequency regions. Experiments were conducted on Terravic database [33], and the best-reported recognition accuracy was 95%.

A significant problem in face thermal biometrics is the high impact of emotional and health status of a person on body temperature and thus thermogram. The solution for this disadvantage is proposed in [34] where infrared thermal imaging was combined with an optical recording. Similarly, in [35], a comparative analysis of the thermal and optical images was conducted but authors have used one sensor capable to simultaneously record optical and thermal images (CCD and LWIR microbolometer), unlike the previous methods where images were taken by two separate sensors. Authors have shown that eigenfaces, and ARENA [36], perform differently when brightness on visual images was changed while on the thermogram there was no impact.

A whole series of weaknesses regarding the use of thermograms for face recognition is given in [37]. Some of the mentioned shortcomings are the high cost of the thermal imaging system, low-resolution of thermal sensors, high noise in the images and high sensitivity on the glass, as the glass is an obstacle to recording thermograms due it's reflectivity. In [38] authors deal with the problem of thermal face recognition with existing glasses. Glasses hide some parts of the face and negatively influence recognition accuracy. Proposed system besides common fazes as preprocessing, face alignment (eyes and lips), detection and extraction of facial features detects glasses. Because of the symmetry of the face, only requires detection of the left part of the face (with and without glasses in thermal images). Reported results of the 1 to N comparison are best when the fusion of visual and thermal images is performed with the low-pass filter. With thermal images reported result is 82% while in case of fusion achieved recognition rate is 90% without glasses and 97% with glasses.

The traditional methods for thermal face recognition mainly concentrate on the hand-crafted features that require significant efforts for selection and extraction of features and usually has relatively lower recognition rate. In [39] a convolutional neural network (CNN) architecture for thermal face recognition is proposed. Similar architectures for thermal face recognition based on CNN followed [40].

Experiment results on RGB-D-T face database [41] show that proposed CNN architecture achieves higher recognition rate compared with the traditional features such as LBP and HOG. In [42] the authors presented a NIRFaceNet, Fig. 7, that is modified from GoogLeNet, but has a more compact structure (only 8 layers and without fully connected layers) and achieves identification rate of 98,48%.

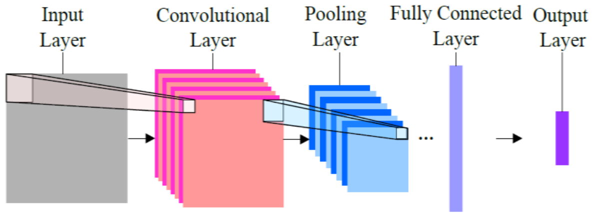


Fig. 7 Structure of a convolutional neural network (CNN) [42]

The use of CNN and Fast Wavelet Transform (FWT) is presented in [43]. An ensemble of classifiers and feature extractors is explored in [43], to reduce errors in face recognition from poor lighting and spoofing. They used CNN tools from, Rasmus Berg Palm's, deep learning tool box [44] and formed a deep neural network of 6 layers; an input layer, 2 convolution layers, with 2 subsampling layers and an output layer. Achieved results showed a mean percentage classification error of 0.84%, on Terravic Facial Infrared Database [45]. When the images where pre-processed with PCA, LDA and KNN, a mean percentage classification error of 0.68% was achieved.

In [46] deep neural network Inception v3 [47] was used for face detection and tracking of elderly people and patients from low resolution thermal images acquired with a portable camera (Lepton thermal camera). For the training 11714 thermal face images recorded with Lepton thermal camera and 73905 other thermal images were used. The best reported result of true positive are 89.2%.

To increase reliability of biometrics systems, research trends are fusion of visible and thermal images, cross-spectral, multi-modal and heterogeneous systems [48]. In [49] a Tensorflow framework for the face recognition called TV-GAN (Thermal-to-Visible Generative Adversarial Network) is presented that is able to transform thermal face images into their corresponding VLD (Visible Light Domain) images in order to maintain an identity information sufficient enough for VLD face recognition models.

In [50] authors have explored if features from a CNN pre-trained on visible spectrum face images can be used to perform heterogeneous face recognition. They explored different metric learning strategies to reduce the discrepancies between the different modalities. Experimental results showed that CNNs trained on visible spectrum images can be used for heterogeneous recognition with near-infrared images and sketches and reported results that are state-of-the-art.

IV. THERMAL FACE IMAGE DATASETS

In the evaluation of recognition methods, significant role plays datasets that are used for training and testing of the model. Datasets differ according to IR band, quality of thermal cameras, recording distances, number of recorded subjects, setup of recording environment, illumination variation, pose changes, facial expressions, glasses, etc. Some authors have created their own datasets. For example, in [7] a dataset is created for each IR band and for visual images with different recording setup and different time period. SWIR images are recorded in controlled and semi-controlled indoor and uncontrolled outdoor environment with distances from 60 to 400 m. MWIR images were created indoor using FLIR camera at a distance of approx. 1,95 m during 20 days. The same distance of 1,95 m but from three viewpoints (frontal, 45° and profile) was used in [10] for SWIR data set. Even smaller recording distance of 0.62 m was used in [9] for the recording of 17 persons sitting on the chair.

IRIS Thermal/Visible Face Database [37], Equinox [25] and Laval University dataset [24] become benchmark facial image datasets (Visible, SWIR, MWIR, LWIR) with images recorded under several scenarios - with the presence of glasses, different facial expressions, etc. A concise representation of representative thermal face datasets with respect of IR band coverage are given in Table 1. In Table 2. datasets for thermal face expression task are listed.

Table 1. Thermal face biometrics datasets with respect of IR band coverage

NIR	SWIR	MWIR	LWIR
	Laval University multispectral face database [24]		
West Virginia University dataset: [7] (NIR: 30- 120 m distance, outdoors, at night time, time period of 20 days; SWIR: controlled and semi-controlled environment, 50 subjects, over two sessions; distances of 50 m and 106 m; uncontrolled outdoor environment, day and night, 16 uncooperative subjects, multiple sessions, distances from 60 to 400 meters; MWIR: live face capture configuration, distance 2 m, indoors, 50 subjects, 15 full frontal face)			[31] 20 persons, indoor/outdoor; face variations: front, left, right; glasses, hat
CASIA database: [51] 197 persons, 3940 pictures, different head poses, glasses, different expressions.	**Cincinnati Electronics** [27] distance: 1,95 m; head poses; 288 images	**IRIS dataset**: [37] 30 subjects, 4228 pairs of thermal/visible images, 11 roughly matching poses; illumination variations	

Table 2. Thermal face expression datasets

Dataset	IR band	Description
Equinox database [24, 26]	SWIR-LWIR	controlled conditions, illumination changes, facial images with and without eyeglasses, 91 subjects 4-second (40 frames) video sequence, subjects pronounced the vowels; facial expressions: smile, frown, surprise; 3 positions: frontal, left lateral, right lateral.
RGB-D-T face dataset [41]		51 persons, 900 images/subject, total 45900 images, controlled, varying rotation, illumination and facial expression
NIST database [34]	Visible and LWIR	image pairs; total: 25.000 frames from 91 subjects; face expressions: pronounced the vowels, smile, frown, surprise, with and without glasses
University of Notre Dame: [44]	LWIR	82 subjects, 2,293 images; face expression: neutral, smiling, laughing; lighting change; time-lapse
[31]	LWIR	76 individuals; different pose and facial expression: happy, surprise, fear, etc.
[9]	LWIR	Distance 0,62 m; 17 persons, emotion type without changing head orientation, different views

Discussion

In reviewed methods authors have experimented with all IR bands. Presented results show that recognition rate depends on various parameters (facial features, classification algorithms, dimensionality reduction methods, etc.). The highest recognition accuracy was achieved in SWIR band (100% for frontal face image) in controlled indoor conditions and with fully cooperative persons. Most methods use LWIR band since energy emitted by the human body is highest in that band and reported accuracy rate comes up to 95 %, even with pose change and different illuminate conditions.

The main advantage of thermal face biometrics and thermal images is invariance to illumination, as they can be recorded in dark and under reduced visibility conditions. But, the limitation is small recording distance since accuracy rate decreases with the increase of distance. Other drawbacks are glass sensitivity and impact of health and emotional state on the thermal images. A proposed solution to overcome these problems in facial thermal biometric is a fusion of visible and IR images and use of CNNs.

V. Conclusion

The use of IR thermal imaging for thermal facial biometrics has attracted recent research and commercial attention as an alternative to visual spectrum based security systems. Unlike the visible light cameras, IR thermal sensors could facilitate greater robustness to illumination changes and can operate in dark environments. Also, IR images can capture new anatomical and physiological face information, such as a structure of the blood vessels and facial vascular network and thermal face signature, that can be used as a unique biometric feature for each person.

Due to the special features of the IR image, two research directions of developing facial recognition methods can be determined. The first relates to the use of physiological features (e.g. vascular networks), and the other to use of multi-modal fusion of complementary data types (e.g. visible and IR). Both research directions are still in their early stages, but the use of CNN and deep learning will further contribute to improving the results.

Achieved an accuracy of thermal face recognition methods are rather high but the need for increased accuracy still exists since in security systems high accuracy is essential because even the smallest error can impact on national security, access control, and similar threats.

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