Human Ear Detection in the Thermal Infrared Spectrum

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ABSTRACT

In this paper the problem of human ear detection in the thermal infrared (IR) spectrum is studied in order to illustrate the advantages and limitations of the most important steps of ear-based biometrics that can operate in day and night time environments. The main contributions of this work are two-fold: First, a dual-band database is assembled that consists of visible and thermal profile face images. The thermal data was collected using a high definition middle-wave infrared (3-5 *microns*) camera that is capable of acquiring thermal imprints of human skin. Second, a fully automated, thermal imaging based ear detection method is developed for real-time segmentation of human ears in either day or night time environments. The proposed method is based on Haar features forming a cascaded AdaBoost classifier (our modified version of the original Viola-Jones approach[1] that was designed to be applied mainly in visible band images). The main advantage of the proposed method, applied on our profile face image dataset collected in the thermal-band, is that it is designed to reduce the learning time required by the original Viola-Jones method from several weeks to several hours. Unlike other approaches reported in the literature, which have been tested but not designed to operate in the thermal band, our method yields a high detection accuracy that reaches $\sim 91.5\%$. Further analysis on our dataset yielded that: (a) photometric normalization techniques do not directly improve ear detection performance. However, when using a certain photometric normalization technique (CLAHE) on falsely detected images, the detection rate improved by $\sim 4\%$; (b) the high detection accuracy of our method did not degrade when we lowered down the original spatial resolution of thermal ear images. For example, even after using one third of the original spatial resolution (i.e. $\sim 20\%$ of the original computational time) of the thermal profile face images, the high ear detection accuracy of our method remained unaffected. This resulted also in speeding up the detection time of an ear image from 265 to 17 milliseconds per image. To the best of our knowledge this is the first time that the problem of human ear detection in the thermal band is being investigated in the open literature.

Keywords: Thermal Imaging, Ear Detection, and Cascaded AdaBoost Classifier

1. INTRODUCTION

Automated methods of recognizing an individual are based on measurable human body characteristics. However, different biological characteristics exhibit both strengths and weaknesses. For example, fingerprints and irises can result in high recognition rates but in order to be measured accurately they require controlled conditions and the subjects need to interact cooperatively with a device. In applications where remote recognition is necessary (such as in the military and law enforcement), face and ear biometrics are more convenient to be measured.

The ear biometric especially has certain advantages: ears are relatively static in size and structure over each individual's life, and unlike human faces, they are unaffected by facial expressions.[?] A typical 2-D ear biometric recognition system has three main stages (as shown in Fig. 1):

1. *Ear Detection (segmentation)* - The ear region is localized in a given 2D image. Further segmentation for edge localization is a second level of segmentation that is required by some ear-based feature extraction methods.

2. *Feature Extraction* - Ear-based features are extracted using certain attributes such as Iannarelli's 12 geometrical measurements.[2] Most of the current ear-based recognition approaches are mainly concerning the feature extraction stage.

3. *Matching* - Once the gallery ear features are properly extracted, they are matched against the probe features, to take a decision about the subject's identity.

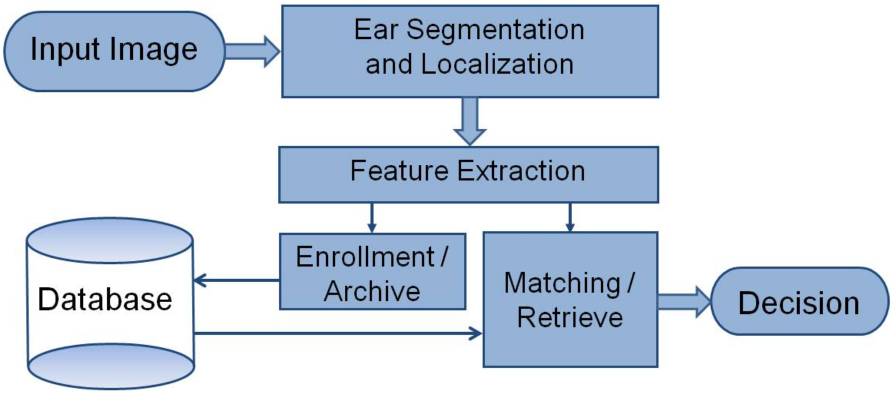

Figure 1. Ear recognition system

Most of the current ear-based recognition approaches are mainly concerning the feature extraction stage in the visible band. In addition, current methods require controlled imaging conditions, assuming that the image is a single head profile in front of a flat background, in order to achieve good recognition rates. Another issue is that in the current literature there is no well-established scheme for automatic 2-D ear detection:[3] reported ear detection approaches depend on manual or semi-automatic methods.[4]

Methods that handle the problem of *fully automated* ear detection include:

- Template matching,[5,6] where the ear was modeled by its external curve; while Chen and Bhanu[7] fused skin-color from color images and edges from range images. In the range images, they observed that the edge magnitude is large around the ear helix and the antihelix parts. They clustered the resulted edge segments and deleted the short irrelevant edges.
- Morphological operators,[8] where the images were filtered using top hat transformation, and the connected components were labeled after thresholding.
- Cascaded AdaBoost based of Haar features,[9–11] a technique that is widely known in the face recognition society as Viola & Jones approach.[1]

1.1 Motivation

The common drawback of the aforementioned approaches is that they were designed to operate in the visible spectrum only. In order to establish such an observation, we performed a set of experiments where we used the discussed ear detection approaches on profile face images acquired in the thermal band. Experimental results illustrated that the ear detection accuracy was as low as 2% (as shown in section 4).

In Fig. 2 we illustrate why designing ear detection techniques to work in the thermal domain is important. We can see that the main advantage is that we can operate in both day and night time environments. The above observations as well the potential future applications in law enforcement and the military, were the main motivation for our work. To the best of our knowledge, this paper represents the first attempt in the literature to investigate the problem of ear detection in a specific range of the passive infrared (thermal) band, i.e. the mid-wave infrared (MWIR) band (3-5 μm).

1.2 Most Related Work in the Thermal Band

By operating in the thermal band[12] the main benefits are: (a) images are acquired without any external illumination in day or night environments, and (b) background clutter is not visible, and thus the tasks of detection, location, and segmentation of various biometric trains (such as ears) can be easier and more reliable than when operating in the visible band. The importance of using the MWIR band for detection and human recognition has been also discussed in[13].[14] In,[13] the authors

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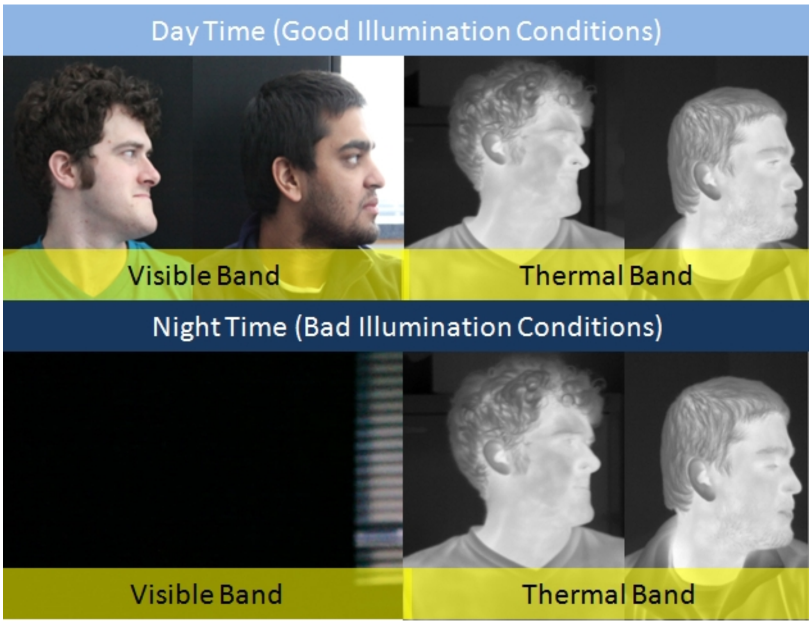


Figure 2. Sample images of two subjects acquired in day time and night time conditions, using a visible and a thermal camera.

studies the problem of eye detection in the Middle-Wave Infrared (MWIR) spectrum was studied. The main challenge was that in the MWIR domain limited features can be extracted from the eye region, mainly eyelashes and eyebrows, while features such as human irises, pupils, and superficial blood vessels of the conjunctiva are not clear. The main conclusion of the work was that human eyes on still frontal face images captured in the MWIR wavelength band can be detected with promising results.

In the same work as well as in[14] the authors discussed also the problem of face identification in the MWIR band and illustrated the advantages and limitations of intra-spectral (MWIR to MWIR) matching using only indoors data, intra-spectral matching using indoors vs. outdoors data, and cross-spectral (visible to MWIR) matching (controlled conditions). The authors showed that MWIR face images can efficiently be matched to MWIR face images (same session) using both research and commercial software (originally not designed to address such a specific problem). However, they also illustrated that matching MWIR to MWIR images from different sessions, as well as cross-spectral (visible to MWIR) matching are very challenging problems.

The aforementioned work identified a new field of research using MWIR as a very useful band that has many advantages over other bands. There are definitely some challenges, as discussed above and below in Section 2.1. However, addressing those challenges will assist many future law enforcement and the military operations.

1.3 Our Approach

We address the aforementioned limitations by designing a thermal-based ear detection methodology that is based on the cascaded AdaBoost framework. The main benefit of our methodology is computational time. In typical ear detection methods[9,10] the computational time for training is several weeks. In our proposed cascaded AdaBoost framework training time requires only of a few hours, i.e. about 100 times faster than the original system proposed by Viola & Jones.[11,15]

The capabilities of our ear detection method are evaluated on the Visible-Thermal Profile Face (VTPF) database that consists of face images of 35 subjects (see Fig. 2). Three different experiments have been performed. The *first* experiment investigates the detection accuracy of our method on the thermal dataset of the VTPF database. The results are compared to those acquired when applying our method using the visible (baseline) dataset of the VTPF database. The proposed method is also compared to other reported ear detection methodologies (originally designed to operate in the visible spectrum).

Although the thermal IR images are robust to lighting variations, their representation changes after applying different normalization techniques. The reason why photometric normalization (PN) was considered in this study is because in[13,14] PN proved to be useful for both MWIR eye detection and face recognition studies. Thus, in the *second* experiment, we investigate the effect of photometric normalization techniques (applied on thermal profile images) on detection accuracy. Finally, we know that the efficiency of detection and recognition algorithms can be significantly affected by the spatial resolution of face images. Thus, we performed a *third* experiment in order to determine the trade-off between ear-based detection efficiency and spatial resolution.

1.4 Paper Organization

The rest of the paper is organized as follows: Section 2 describes the hardware used in data collection and the acquired database. Section 3 presents the proposed ear detection system. Section 4 describes various experiments to evaluate the proposed technique, and Section 5 provides concluding remarks, and sketches our plans for future work.

2. THERMAL IMAGERY

The thermal camera used in this work is a high definition Middle-Wave Infrared (MWIR) camera produced by FLIR Systems*. It is capable of acquiring thermal imprints of human skin and analyzing the thermal distributions and temporal variations. The camera is capable of generating high definition thermal images and operating in diverse testing environments. It features a high resolution 1024×1024 Indium Antimonide (InSb) Focal Plane Array (FPA) achieving mega-pixel image resolution in a single thermal image. The spectral range of the camera is 3-5μm, and it has a 14 bit dynamic range and a Noise Equivalent Temperature Difference (NEDT) of less than 25mK. The camera was outfitted with a 50 mm MWIR lens also provided by FLIR Systems.

The aforementioned thermal system was employed for data collection in order to assemble, as part of a pilot study, the Thermal Profile Face (TPF) database (see Fig. 3). The standoff distance was set to 10 feet. The database was assembled on a single session spanning over a time period of 20 days. In the beginning of the session, the subjects were briefed about the data collection process after which they signed a consent document. In total, 35 subjects (24 male + 11 female) participated in this experiment, and the database has 20 right and left (40 in total) profile face thermal images of each subject, resulting in a total of 1,400 images.

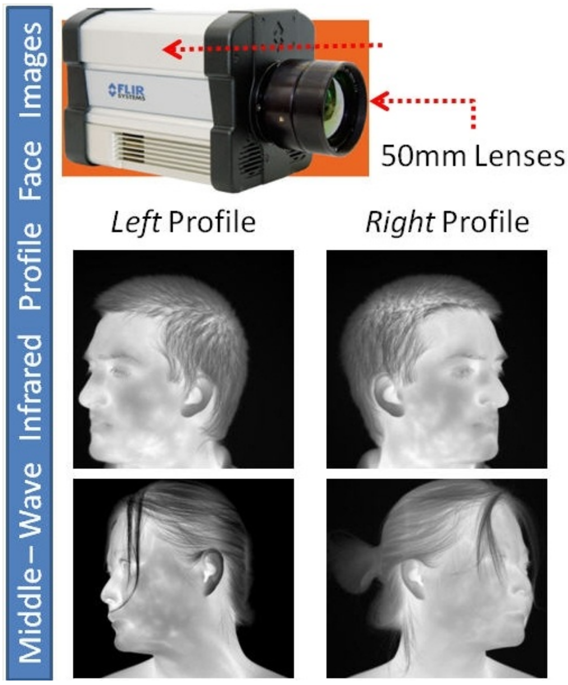
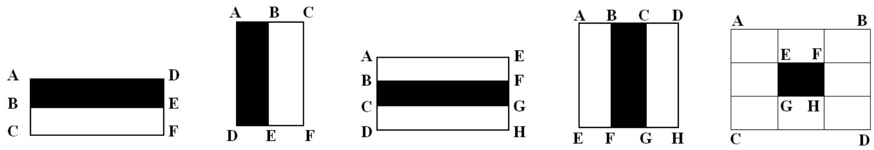


Figure 3. Thermal camera setup and acquired sample profile face images. Note that originally the camera acquires video frames where each pixel has a temperature value ranging from ∼24-41 degrees Celsius. Then these frames are converted to gray-scale images for display purposes.

*"FLIR Systems," http://www.flir.com, 2011.



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

Figure 4. Example of the used rectangle features. These simple features are based on the Haar basis function: (i) two-rectangle (a,b,e), and (ii) three-rectangle (c,d).

2.1 Issues with Acquiring MWIR Face Images

While the target was to collect only full profile images ($+/-90^o$ head yaw) some subjects did not follow the exact data collection protocol. This resulted in having some sample images with head yaws (y-axis) that range from $+/-10^o$ to $+/-90^o$. Thus, we had to deal with a more challenging problem (i.e., detecting ears under variable poses), since having only full profile data would result in better detection rates. Another issue is the thermal sensitivity of the camera that is an important factor since it impacts image quality, i.e., the lower the sensitivity, the more accurate the camera can be in order to produce higher quality images. The camera that we are using has the highest sensitivity in the market. The associated software of the camera was used to perform regular calibration (before acquired each set of thermal profile images), which ensures that the camera operates to its optimum performance, and as a result it guarantees measurement accuracy and reliability. The camera operated in a controlled, low temperature environment (room temperature) where better thermal sensitivity can be exploited since the thermal contrast (temperature delta within an image) is very low. An additional software tool (provided by FLIR) was used to remove noise (e.g, dead pixels) from face images and control the temperature scale limits (e.g., setting the temperature range from 28^o to 41^o Celsius that is the typical range of human body temperature) during data collection.

Another issue is dealing with noise factor when acquiring thermal images. It is well known that the thermal images are sensitive to environment and human body temperature. Thus, the thermal sensitivity of the camera is an important factor since it impacts image quality, i.e., the lower the sensitivity, the more accurate the camera can be in order to produce higher quality images. The camera that we are using has the highest sensitivity in the market. The associated software of the camera was used to perform regular calibration (before acquired each set of thermal profile images), which ensures that the camera operates to its optimum performance guarantees measurement accuracy and reliability. The camera operated in a controlled, low temperature environment (room temperature) where better thermal sensitivity can be exploited since the thermal contrast (temperature delta within an image) is very low.

3. EAR DETECTION SYSTEM

The proposed ear detection procedure classifies images based on the value of rectangular features, as shown in Fig. 4. These features encode ad-hoc domain knowledge, and can work faster than pixel-based ones.[1] The value of each rectangle feature is the difference between the sum of the shaded and the white regions. For cases where the white and shaded regions are not equal (see Fig. 4 (c,d,e)), we compensate by subtracting a multiple of the shaded area, e.g., for Fig. 4(e), the shaded area is covering 1/8 the white area, thus the *value* of the *rectangle feature* is equal to *white-8·shaded*. Based on the average ear length and width ratio, we decided the base resolution of the ear detector to be 24×16 pixels. The complete rectangle feature set used in this paper (including all possible scales and shifts) consists of $58,428$ features. Each rectangle feature *f* represents the main component of the weak classifier $h(x, f, p, \phi)$, where ϕ is a threshold, and *p* is the polarity indicating the direction of the inequality:

$$h(x, f, p, \phi) = \begin{cases} 1 & \text{if } p \cdot f(x) < p \cdot \phi \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The learner is called a weak classifier due to its low performance. Each ensemble classifier consists of a set of *T* weak classifiers, where θ is the threshold of the ensemble (strong) classifier:

$$H(x) = \begin{cases} \text{Continue} & \sum_{t=1}^{T} \alpha_t \cdot h_t(x) > \theta \\ \text{Reject} & \text{otherwise} \end{cases} \tag{2}$$

These ensemble classifiers have a cascade arrangement forming the ear detection system (see Fig. 5).

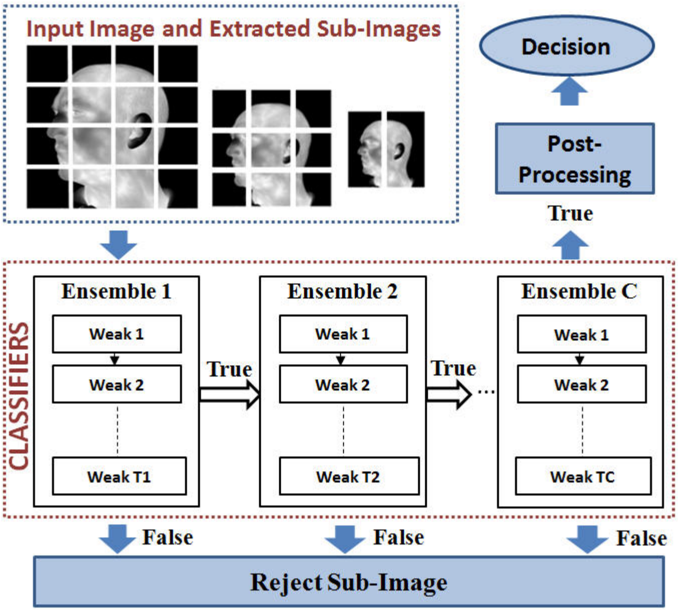


Figure 5. Overview of the ear detection system: An input thermal image is scaled multiple times. For each scale a set of all possible 24×16 pixel sub-images (including overlapping ones) is extracted. Then each sub-image is evaluated through a cascaded AdaBoost classifier, after which a decision about the location of ears (when detected) is made.

3.1 Training stage

The proposed system is trained based on the fast training method proposed by Wu et al.[15] that is capable of significantly reducing the computational complexity the training phase of the naive AbaBoost classifier[1] by two orders of magnitude. The modification suggested by Wu et al.,[16] is to store M feature values of the N samples in an $M \times N$ matrix, and sort these features only once. This approximately cut the complexity by $\frac{1}{T}$ via taking the sorting block outside the feature selection.

Our classifier was trained by a number of manually segmented ears (1,428 in total) from the left and right profile thermal images database. For the non-ear segments, we used 2,334 segments that were randomly extracted from thermal images. Viola and Jones[1] simplified the optimization problem of the learning procedure, by choosing a target accuracy. They fixed the maximum False Accept Rate (FAR) and the minimum Detection Rate (DR) of the overall system of C ensembles, where:

- FAR $< (far_{max})^C$,
- DR $> (dr_{min})^C$

To make the detection system faster, for the first few ensembles we kept a very low number of features. We sacrifice the far_{max} for these ensembles, while we boost the overall FAR by increasing the number of stages as required.

3.2 Post-processing stage

In order to detect an ear in an input image, the image is scanned using the proposed cascaded AdaBoost system. This means that the input image is divided into overlapped sub-images of 24×16, and each region is evaluated. Then, the image is scaled down by a factor $s = 0.8$ and the process is repeated. At this post-processing stage, all the detected regions at various levels of the scale pyramid are scaled back to the original image resolution. Then, the overlapped detected regions are combined into a single rectangle region.

3.3 Evaluation criteria

The criteria used to evaluate the effectiveness of our ear detection system are the following:

- False Reject Rate (FRR): is the frequency that ears are rejected, i.e. the number of falsely rejected ears over the total number of ear segments present in the input images;
- False Accept Rate (FAR): is the frequency that non-ear regions are falsely accepted as ears, i.e. the number of images having falsely accepted ears over the total number of images. This false alarm is also raised when the system detects multiple images of the same ear that the post-processing stage was not able to filter.
- Equal Error Rate (EER): is the operating point where the FRR equals the FAR, or practically the point of minimum difference between FAR and FRR.

4. EXPERIMENTAL RESULTS

The proposed ear detection system was tested using a different than the training sub-set of 480 images from the (TPF) data set. Various experiments were performed to test the ear detection system (as described in Section 1). The final detector consists of a 28 cascade of classifiers that result in a total of 4,132 features. Four experiments were conducted.

- **Eye Detection using MWIR or Visible Data**: In the *first experiment*, we tested our algorithm on two different scenarios, i.e., when MWIR images are used for training and testing (ideal for day/night time environments), and then visible images are used for training and testing (day time environment or baseline conditions). The second scenario was investigated to illustrate that our method has the capability to be applied in both the visible and MWIR band. In the *former scenario*, we established that when using only MWIR profile face images, our cascade AdaBoost detector achieves a detection accuracy of 91.25%, yielding 42 missed ear segments (31 were missed due to pose), and 15 false alarms. In the *latter scenario (visible data)*, our ear detector[11] uses a 19 layer cascade of classifiers, which included a total of 2332 features. We tested the visible ear classifier using 660 visible profile face images from the VTPF database, yielding a detection accuracy of 95.15% and 7 missed ear segments.

  To construct the Receiver operating characteristic (ROC) curve between the FAR and FRR, cascades were removed one by one. The ROC curve for our the thermal-based ear detector (blue dotted line) is illustrated in Figure 6. In the same figure we can see the ROC curve (red dotted line) resulted by applying our method on the visible images of the VTPF database (baseline experiment). In this case the detection rate reached 95.15%. However, the limitation here is the fact that ear detection can operate only in day-time conditions.

  Figure **??** illustrates some examples of correctly detected ear in both the visible and thermal band when using the proposed method. We can see some challenging scenarios where ear detection did not work, i.e., cases where the head pose was near full frontal or there was an ear occlusion due to hair. Figure 7 (i) illustrates some examples of correctly detected ear in the MWIR band, even in the presence of multiple subjects and even with the presence of partial head.

Table 1. Detection performance when applying our ear detection technique on the thermal data set after applying several Illumination Normalization techniques. Results are compared to the baseline scenario, i.e., when using the visible data set. Detection rate (i.e., 100-FRR) and FAR.

$Scenarios$	$Detection\ Rate$	FAR
$Visible\ (Baseline)$	95.15	1.06
$Thermal$	91.25	3.13
$Thermal + HE$	78.12	4.58
$Thermal + CLAHE$	89.79	23.33
$Thermal + DCT$	41.04	0.42
$Thermal + WA$	65.00	0.63

- **Effect of Photometric Normalization on MWIR Eye Detection**: In the *second experiment*, we investigated the effect of photometric normalization on detection accuracy. The thermal profile face images were pre-processed using several normalization techniques. Fig. 7 (ii) shows the effect of photometric normalization using: (a) histogram equalization (HE), (b) contrast limited adaptive histogram equalization (CLAHE),[17] (c) DCT based normalization (DCT)[18] and (d) wavelet based normalization (WA)[19] respectively. Table 1 summarizes the results. We can see that the normalization has a negative impact in the detection efficiency of our method. However, we performed another

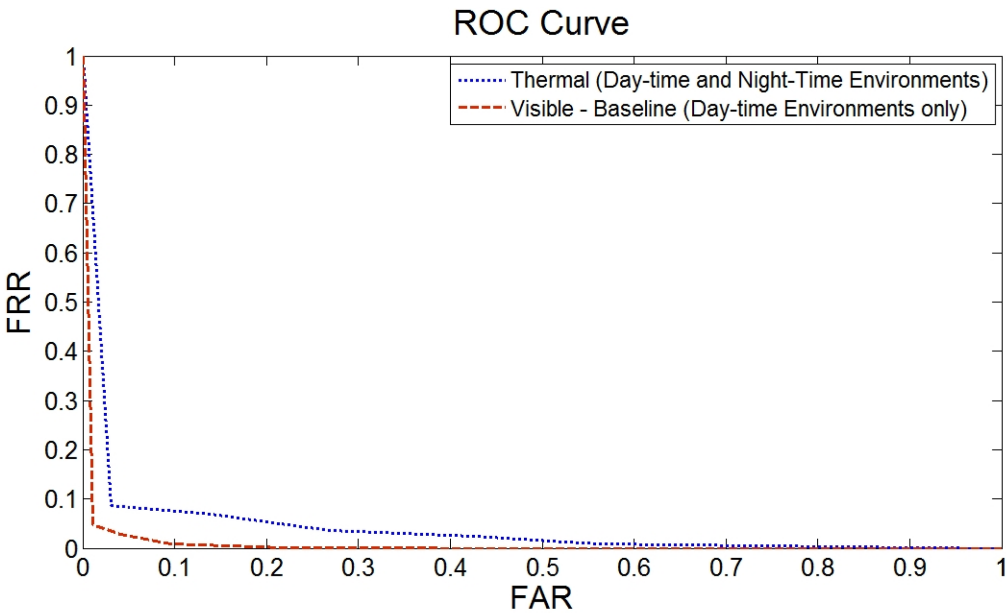


Figure 6. ROC curves showing the accuracy of our proposed thermal-based ear detector. The performance is comparable to the baseline scenario, i.e., using visible profile images. The advantage of our proposed approach is that we can detect human ears in both day- and night-time conditions.

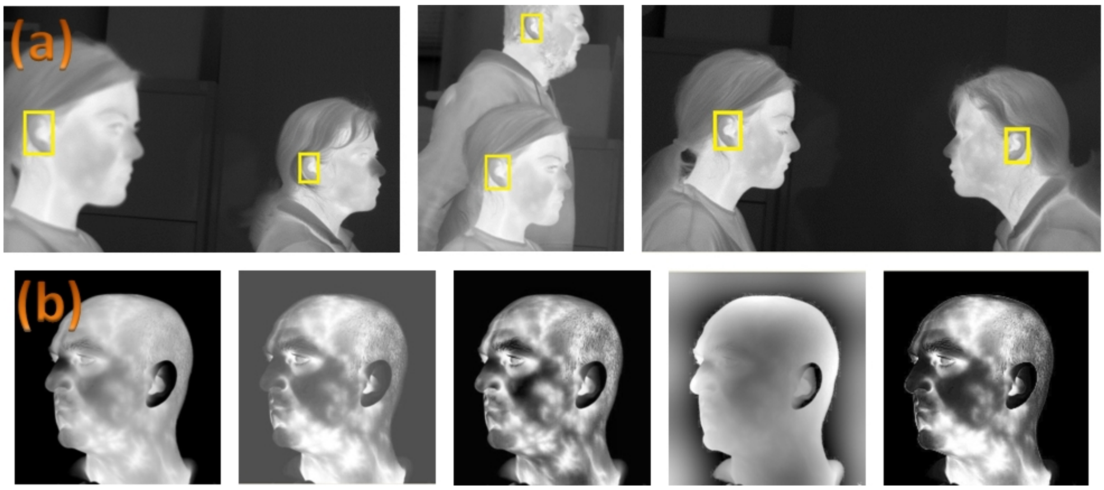


Figure 7. (i) Sample thermal (MWIR) profile images where the ears were (a) correctly detected or (b) missed (falsely rejected) using our proposed method. (ii) A thermal left profile image sample before (a), and after photometric normalization using HE (b), CLAHE (c), DCT (d), or WA (e)

experiment where only the images with missed (no detected) ears were photometrically normalized. It turned out that the normalization lowered down the false rejection rate, by 3.33% for HE while maintaining the same FAR. For the CLAHE, the false rejection rate enhanced by 4.04%, while the FAR increased by 1.96%.

- **Trade-off between Detection Accuracy and Spatial Resolution**: We conducted a *third experiment* to determine the trade-off between MWIR ear detection accuracy and spatial resolution. We used 40 out of the 480 thermal profile face images (left and right) of the test set. Figure 8 shows the effect of spatial resolution on detection performance and memory management. We determined that the breaking point appears to be at a resolution around 137×137, that results in approximately 1/9 of the total number of pixels of the original resolution (410×410). When the 137×137 resolution was used, we managed to achieve 100% detection accuracy while lowering down $\sim$5 times the computational time required for processing the images at the original resolution.

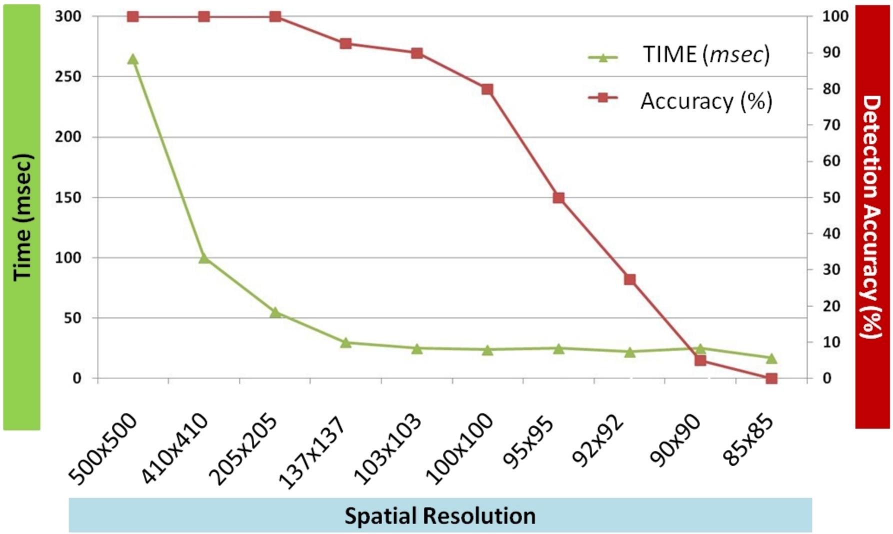


Figure 8. Ear detection performance (when operating in the MWIR band) versus time for various spatial resolutions.

Table 2. Detection performance when applying our ear detection technique on the thermal data. Results are compared to other approaches. Detection rate (i.e., 100-FRR). *This performance comparison is copied from[8]

$technique/Detection\ Rate$	$Visible$	$Thermal$
$Proposed\ Method$	95.15	91.25
$Template\ Matching$	$51.15*$	0
$Mathematical\ Morphology$	$96.46*$	2.25

- **Comparison of our Ear Detection Approach vs. Other Methods (Visible and MWIR bands)**: We compared the efficiency of our method with other approaches in the literature. Table 2 shows the detection performance using visible and thermal data. When template matching[6] was used the detection accuracy was 0%, and 2.25% was achieved when using the mathematical morphology detector.[8] A complete study of the application of our method to visible profile face images has been reported in.[11]

5. CONCLUSIONS AND FUTURE WORK

This paper has presented a study on the problem of ear detection using thermal profile face images (TPF) database. Experimental results show that, unlike previous approaches in the literature that operate only in the visible spectrum, our proposed ear detection method can operate on both MWIR and visible bands with promising results. The proposed method yielded ∼91.5% detection accuracy using images with head yaws (y-axis) that range from $+/-50^o$ to $+/-90^o$.

We also determined that photometric normalization yielded an improved detection rate when it was applied only to falsely detected thermal face images. Finally, we determined the trade-off between detection accuracy and image resolution: using one third of the original resolution the computational speed decreases ∼5 times while retaining the same detection accuracy as the one acquired by using the original resolution.

Although our approach is relatively successful in identifying ears under various rotation angles, it would be desirable to enhance system performance by using extended Haar features as suggested in,[20] or by including in the training set more face images with poses closer to frontal. Another extension of our work would be to extract reliable ear features that can be used for ear recognition using thermal images.

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