Biometrics in infrared/near-infrared band

Satu Alaoutinen

Lappeenranta University of Technology, P.O.Box 20, FIN-53851 Lappeenranta, Finland,
santtu@lut.fi,
WWW home page: http://www.lut.fi/~santtu

Abstract. This paper presents the results of a literature review done on infrared person identification and verification. Paper covers the theoretical background of the infrared recognition and the research done in this area. The research is mostly basic research and only few applicable solutions exist. The main reason is the expensiveness of the required cameras.

1 Introduction

The on-going competition between security officials and criminals forces us to continuously look for new ways to identify persons or authenticate their identity. We need methods that are easy to use, inexpensive, and reliable. Fingerprints have been used for these purposes for a long time. Its drawback is the skin contact needed to get the image. Retinal scan is also a reliable method but getting the image requires some accuracy. People have also a tendency to protect their eyes, so they may have certain reservations against this method.

Some methods have not been used because of their expensiveness. One of these is infrared images. Infrared cameras have been too expensive, their resolution has not been good enough, and the cameras needed too long a time to cool between images. Recent development in CCD and camera technology has made possible to manufacture infrared cameras that do not need cryogenic cooling, function quickly enough, and have high enough resolution for recognition purposes [4].

This paper is a literature review of infrared technology used for biometric person identification and authentication. The paper has been divided into two parts. The first part covers the background and research in thermal infrared band. The second part covers the near-infrared band and a research done at that area.

2 Infrared Band

This section concentrates on research and applications done using the actual infrared band of radiation. The section describes the physical background of the method and goes through its application areas.

2.1 Background

If we would measure the temperatures inside our body and from our skin, we would notice that the inner temperature is higher. Our vascular system locates mainly inside our body and it warms our blood before it circulated under our skin. So, the warm blood comes to the skin, warms it, cools down, and flows back [8]. The effect is that the temperature on the skin just above a vein is about 0.1 °C higher than elsewhere. For example on human face the resultant temperature difference is typically 8 °C, which can be captured by current imaging technology. Also a diameter of an individual vein (~2.5mm) is within the resolution of current technology [7].

On our face and head we have about five kilometers of blood vessels, which form vein patterns that are unique to each individual. Our veins choose their routes by random. The inheritance does not affect the patterns. Therefore, even identical twins have their individual vein patterns (figure 1).

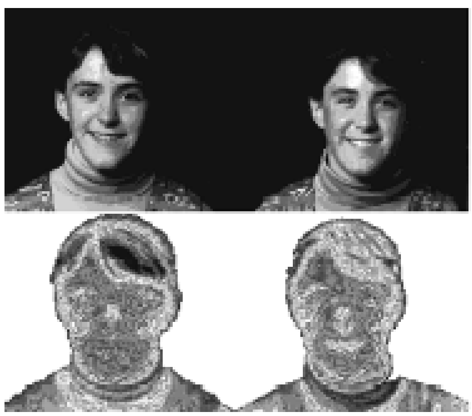


Fig. 1. Thermal contours of identical twins [7]

Infrared imaging pictures heat radiated by a target instead of light reflected by a target. The resulting image is called a thermogram. Though, the vein patterns are generally accepted to be individual, there is now way to proof that the thermograms are discriminative enough. It is however possible to show that they contain more variations than fingerprints. It has also other benefits. It is nonintrusive, it does not require either physical contact to any device or artificial lighting. Therefore people could be expected to accept its use quite easily. However, its main advantage is the independence of the lighting conditions. Because the thermogram images heat radiance, it remains the same even in total darkness [3]. In addition, a color of the skin does not affect the resulting thermogram, neither does the vein patterns change during our life. In one experiment thermograms have been taken from a sample group during eight to 23 year period and no changes were found [7].

However, there are plenty of factors, which can affect the skin temperature [7]:

- changes in ambient temperature
- air flow conditions
- exercise
- metabolic activity
- illness
- drugs
- wearing tight clothing
- being under stress
- having a migraine headache
- blushing
- having an infected tooth

Due to the number of variables, it is difficult to find features which are persistent enough for identification and authentication purposes. Of course, when verifying person's identity, it is easier to control the environment but still some variables exist. The changes in overall temperature can be removed by computing the differences between some fixed point and the others or ignoring the temperature values and concentrating to the anatomical features, like face recognition in visible light.

Also in infrared imaging, the image has to be taken always from a same angle, as is the case with images in visual spectrum. Therefore, the imaging conditions has to be arranged so, that the target is always faced to the camera or the system has a database of images taken from different angles.

It can not be fooled with disguises. If the system can see through it, it will reveal the real identity and if it can not see through it, the system reveals the disguise showing blank [8]. Also, surgical incisions cause alteration of blood vessel flow, which appears as distinct cold spots in the thermal imagery [6].

The thermal radiation cannot fully penetrate glass. In some cases the thermal radiation is blocked totally. This property restricts the areas, where infrared recognition can be used. Figure 2 shows an example of this phenomenon using the mid-infrared waveband (3.0 - 5.0 μm). The passenger can be seen through the side window but through the windshield, nothing can be seen.

2.2 Thermogram

The most common case, where infrared has been used for recognition, is facial thermogram. Initially it has been used for cooperative access control applications. The thermal contours have been matched using metrics, template, fractal, or wavelet methods. This subsection uses as a source [7] if not otherwise mentioned.

The face metrics are the same as used with visual images and some more, which can only be extracted from infrared images using for example specific

Fig. 2. Snapshot of vehicles

vascular references. Infrared imaging does not improve the reliability of face metrics but enables its use in poor lighting conditions.

Another way is to use facial templates (figure 3). Standardizing the thermograms as to size and normalizing the histogram, the areas of canthi and the inner cheeks can be compared using template matching. This method has been used with rather good results.

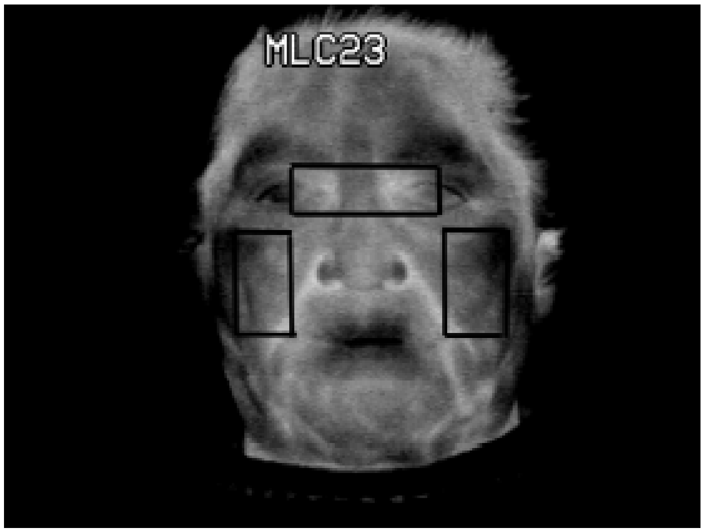


Fig. 3. Face templates

It is possible to see over 100 different closed thermal contours in a human face. A closed contour extracted from an image is called an elemental shape. While matching the shapes in real-time they can be shrinked and enlarged without changing the other features. This set of shapes is unique for every person, including identical twins. This method has achieved 96 % accuracy in real-time cooperative access control applications.

Eigenshape analysis can also be used with elemental shapes. In one experiment, it required 20 hours to do an 11-coefficient eigenanalysis, where each person's image was characterized by a set of 11-coefficient polynomials. All the database images were manually selected from infrared videotapes obtained at trade shows. Only sharp, full face images were selected and manually scaled and centered. This non-cooperative, non-real-time search achieved 98 % accuracy with no false accepts.

According to Prokoski, Unisys Corporation has developed an unattended, cooperative access control system, which used wavelet analysis. The system performance was over 98.5 % even in cases, when persons used eyeglasses some or all of the time. Switching the glasses, however, increased the system error clearly.

Quite recently the research has started to concentrate to recognition of anatomical structures instead of thermal contours. Two approaches in this area are symmetry waveforms and face codes.

At the first glance, human face seems symmetrical but deeper looking reveals some asymmetries. There are six techniques, which rely on the hypothesis that each person's asymmetries are unique to that person. All of them analyze only a vertical area within the outer corners of the eyes and assign a value to each horizontal line of pixels in this slice. So both eyes need to be in sight. Figure 4 is an example of a symmetry waveform.

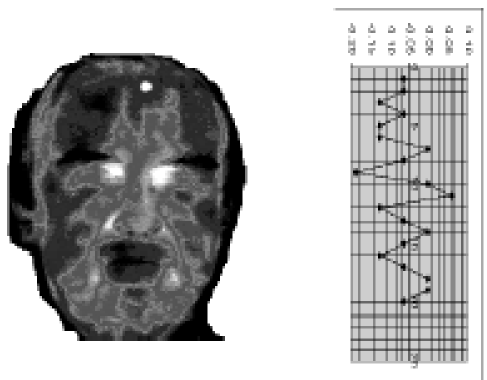


Fig. 4. Symmetry waveform

The methods can be grouped into three groups. First group includes three methods that analyze the gray scale image and produce a waveform which represents:

1. the total grey scale value to either side of the vertical line bisecting the analyzed ares,
2. the x-value at which the total grey values within the swath to either side are equal,
3. the foldover point which provides the smallest cumulative difference between gray scale values to either side of the point.

The next two methods analyze

1. thermal contours
2. vasculature by binarizing the image

and locate the balance point between the above mentioned targets which cross that horizontal. The sixth technique considers minutiae symmetry, finding the best balance point among minutiae along that horizontal. Minutiae are the uniquely differentiating characteristics of the biometric attribute [1]

Face codes can be either one-dimensional bar codes created from a symmetry waveform (figure 5) or two-dimensional bar codes, in which the face is divided into cells and each cell is compared to a face segments. The best matching segment is selected and its code used for that cell. A simple binary code can be generated by dividing the standardized face center into cells and indicating those in which minutiae are present.

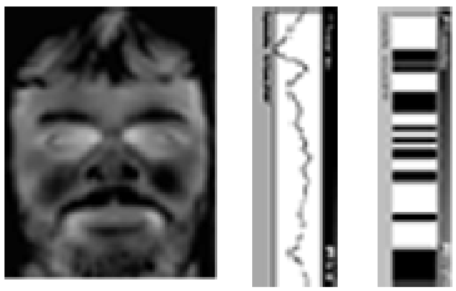


Fig. 5. Bar code derived from a symmetry waveform

A simplest, but efficient method is to downsample an image that has been deskewed, centered, scaled, and histogram normalized. The result is a 32 pixels wide thumbnail image that provide accurate identification and requires little processing.

Thermograms can also be taken from hands [5] and ears to extract physical features.

2.3 Vein pattern

In certain parts of our body the veins are clearly visible and they form patterns, which can be imaged and analyzed (figure 6). Such places are the back of the hand, the wrist, and the face. The purpose is the same as in retinal technology: using infrared light to generate an image of a person's vein pattern [2]. Based on this image a template can be build, with which to try matches against templates already stored. The use of infrared imaging offers some advantages in manufacturing or shop-floor applications where hands may not be clean enough to scan properly using traditional video or capacitance technique [1].

2.4 Comparisons

Not many comparisons exist, where at least some infrared methods have been compared to other biometrics. A research done by Socolinsky et al. [9] compares infrared and visible imagery for face recognition. They have used a long wave infrared band between 8 and 12 μm. All the images have been taken inside and they consider the database representative for such purposes, though, all

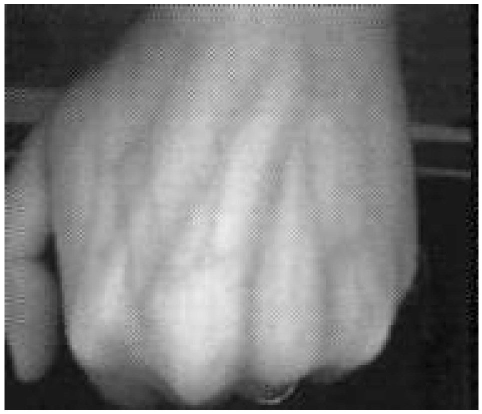


Fig. 6. Infrared image of a hand

the variations possible in infrared images are not present there. They have used four methods for reducing the dimensionality of the set of face images: Principal component analysis (PCA), Linear discriminant analysis (LDA), Local feature analysis (LFA), and Independent component analysis (ICA). As dissimilarity measures they have used six distance functions: L^1, L^2, Euclidean angle, Mahalanobis L^1, Mahalanobis L^2, and Mahalanobis angle. First, each method was tested using all distance functions in turn, in visible and infrared images (figure 7).

Then, using the best distance function for the method, each method was used for recognition, both in visible and infrared images (figure 8).

The results show that LDA-based methods gave the best results in both cases and infrared imagery was clearly more effective than visible imagery. Using infrared the identification errors reduced by over 30 % and EER lowered by over 20 % in verification. They also tested a combination of visible and infrared imagery and the results were even better. The identification errors and EER dropped more than 45 % and 40 % respectively. Figures 9 and 10 show the results using LDA in identification and verification respectively.

The other comparison is rather based on opinions of experts and probably follow the general conceptions about the different biometrics. Table 1, created by Jain et al. [3] describes, how some of the biometric identifiers correspond the desirable properties.

As can be seen from the table, hand vein biometrics place in the middle through the table. Only its circumvention is high. On the other hand, facial thermogram competes with retinal scan. Its weakness is the non-permanence of the property, which causes only medium performance. Its good collectability and acceptability are clear benefits but the expensiveness of the technical equipment makes it less useful.

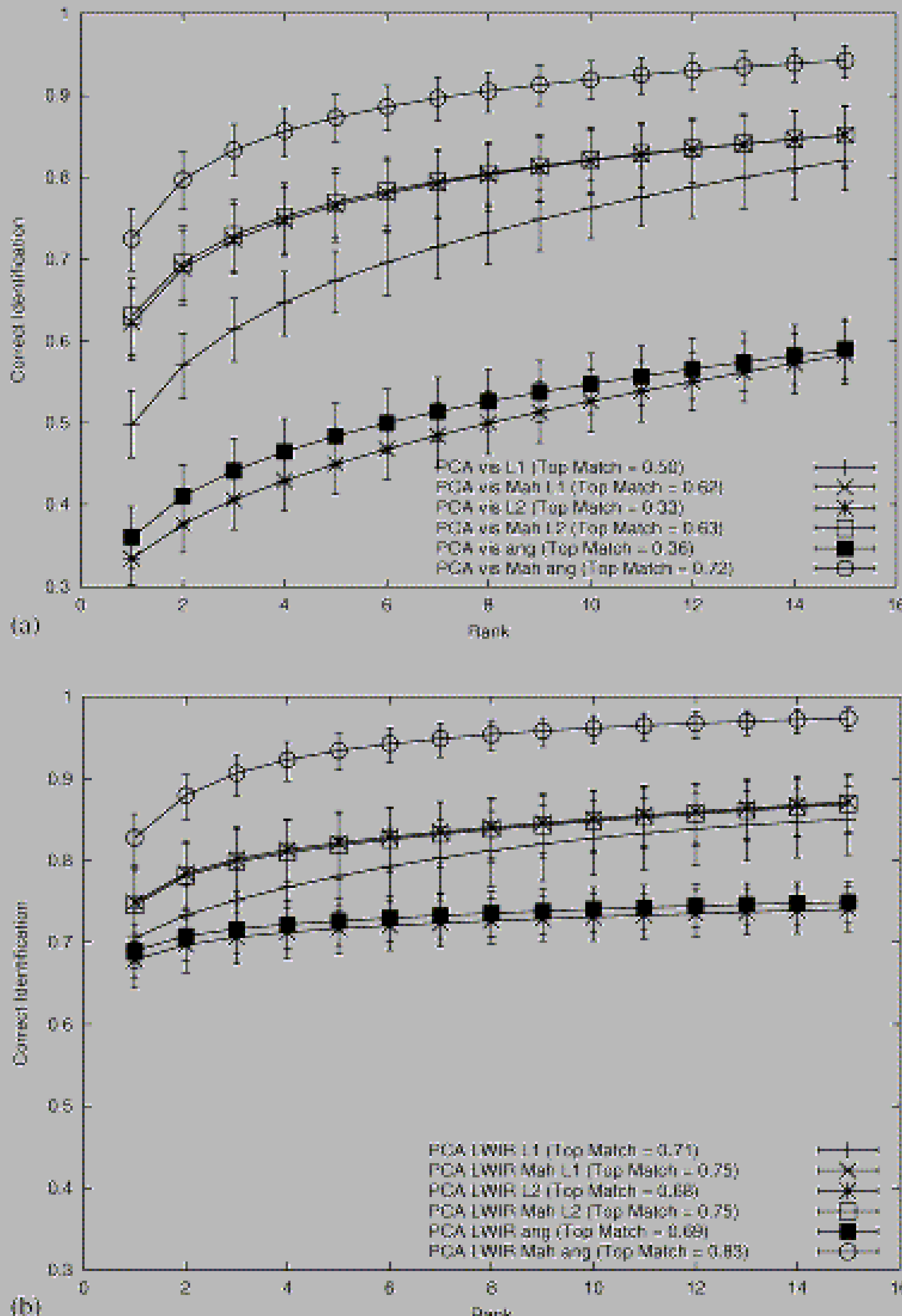


Fig. 7. Cumulative recognition rates for PCA-based identification algorithm on visible (a) and LWIR (b) imagery

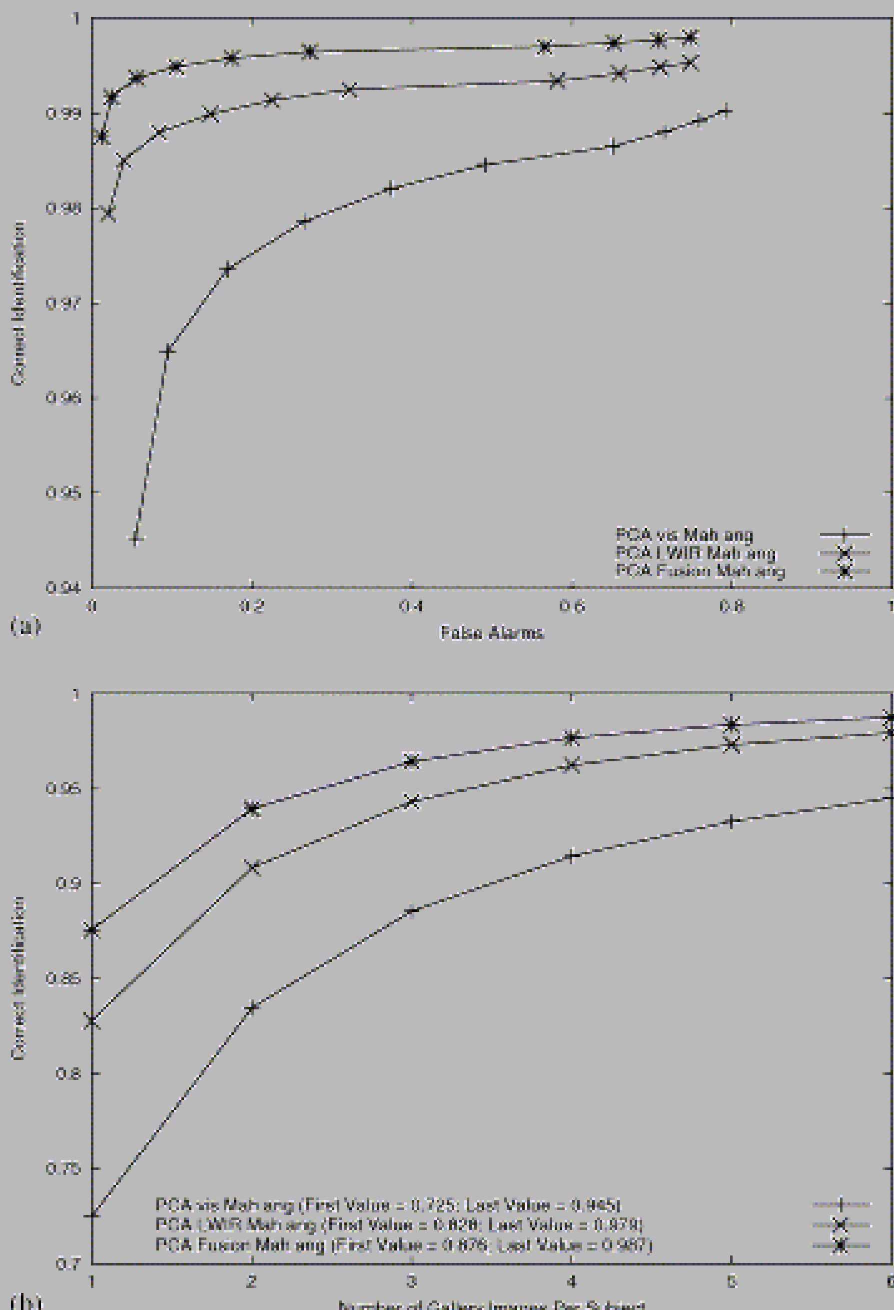
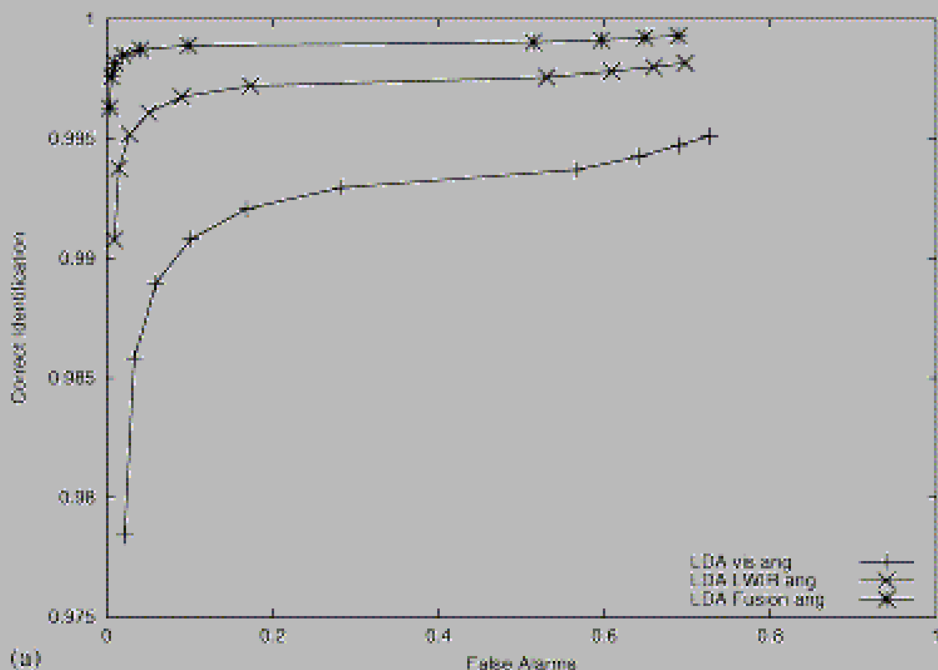
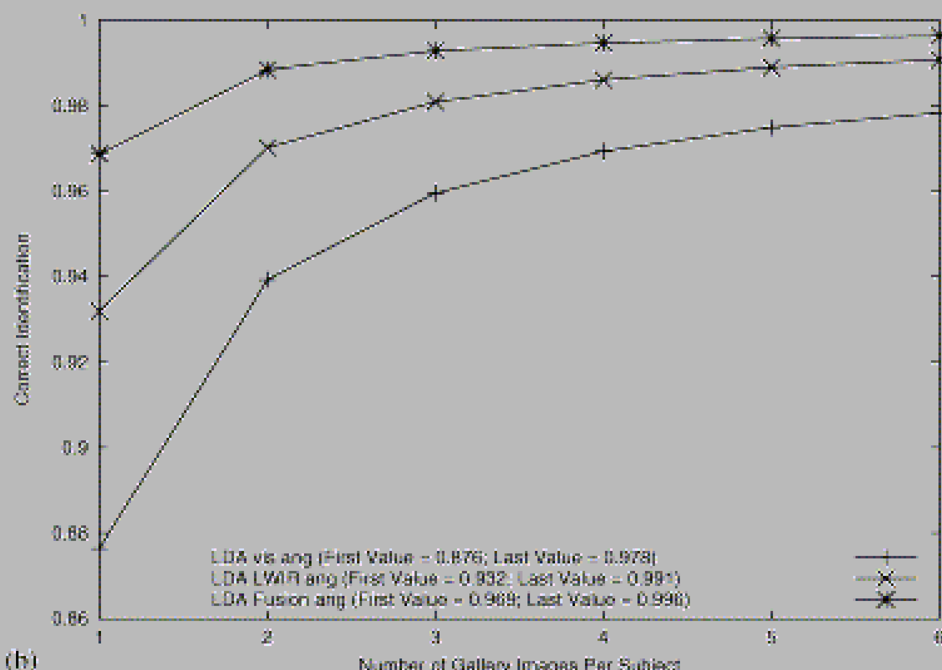


Fig. 8. (a) Identification receiver-operating-characteristic curves for best PCA-based algorithms on visible and LWIR imagery with six gallery images per subject. (b) Top-rank identification performance as a function of number of gallery images per subject

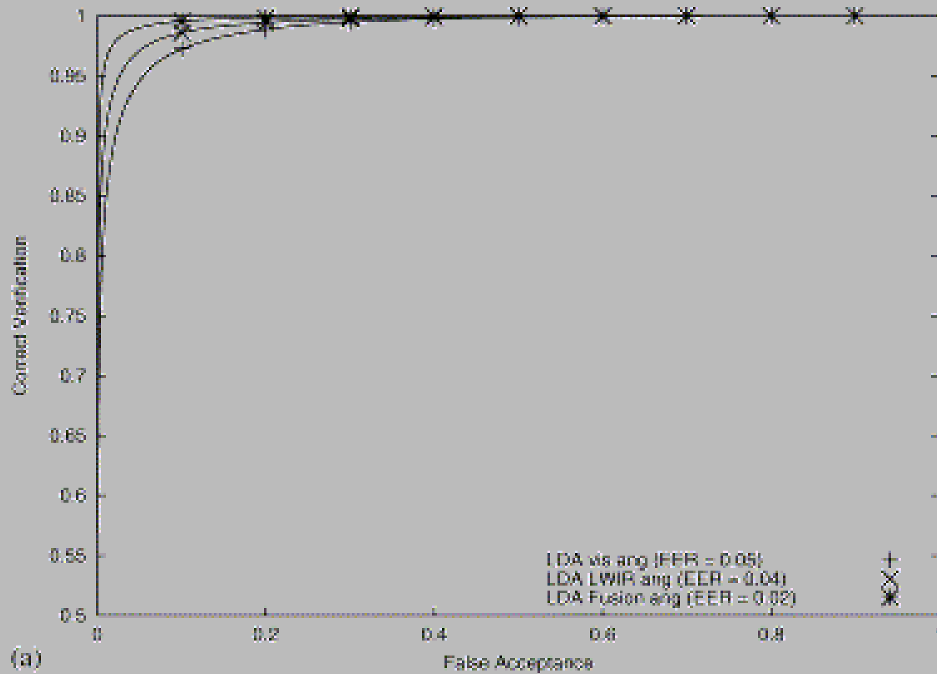


(a)

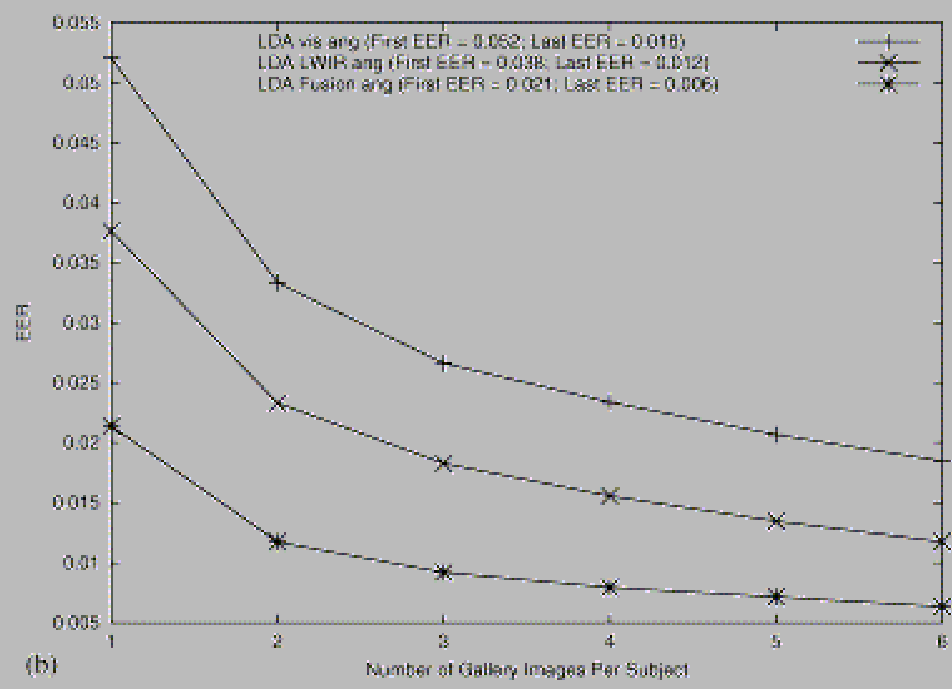


(b)

Fig. 9. (a) Identification receiver-operating-characteristic curves for best LDA-based algorithms on visible and LWIR imagery with six gallery images per subject. (b) Top-rank identification performance as a function of number of gallery images per subject



(a)



(b)

Fig. 10. (a) Verification receiver-operating-characteristic curves for best LDA-based algorithms on visible and LWIR imagery with six gallery images per subject. (b) Equal-error-rate as a function of number of gallery images per subject

3 Near-infrared

In this section I will shortly tell about an interesting research done by Pavlidis and Symosek [6]. They are looking for new solutions for disguise detection and for extracting the targets from the background.

The near-infrared spectrum ranges from 0.7 μm to 2.4 μm and is associated with reflected solar infrared radiation. The thermal radiation does not happen yet in this band. This spectrum provides some unique advantages for the face detection.

– Though, artificial illumination is needed in poor lighting conditions, the illumination is invisible to the human eye. So, there is no risk of dazzling.
– The near-infrared radiation can pass the glass.
– Near-infrared cameras are not as expensive as infrared cameras. However, they are more expensive than the ordinary ones.
– Human skin can easily be detected in near-infrared spectrum. Especially in the range 1.4 - 2.4 μm.

The method uses two cameras, which spectral sensitivities are above and below 1.4 μm. The threshold point does not necessarily need to be exactly at 1.4 μm. It is enough, if the camera spectrums cut somewhere near that point. The crux of the method is the fusion of the co-registered imaging signals from the lower- and upper-band cameras. It is also known that human skin suddenly stops reflecting around 1.4 μm. This makes the skin to naturally extract from the background, not depending of the skin color (fig. 11. As can be seen from the picture, in the lower band, skin looks white and in the upper band black, regardless of the race. The spectra radiance of the sun everywhere else than on the skin is three times more intensive in the lower-band than the upper-band. Therefore the same scene looks three times brighter in the lower-band. In order to get the image fusion work as wanted, this has to be taken into account.

The fusion image is the difference between the two scenes, the upper-band weighted. It is computed pixel by pixel as follows:

$$P(i,j)_{fused} = P(i,j)_{lower} - f * P(i,j)_{upper}$$

The factor f should be around 3. In the final image, only the exposed skin parts of the human body are visible. The background has vanished. In figure 12 the power of the fusion can be seen, when the dummy head disappears.

The fusion method could be used in combination with a traditional visible spectrum face recognition method. It could help the face detection system to better locate the target and its area, as in figure 13, where the visible recognition system is unable to detect the face.

The examples showed that there is very sharp contrast between the human skin and the background in the upper-band near-infrared. The skin is always black. Human hair, however, is highly reflective in the upper-band and appears almost white in the images. The researchers have found that even wigs made of

Fig. 11. Caucasian, African, and Asian people. Row 1: visible band, row 2: upper near-infrared band, row 3: lower near-infrared band

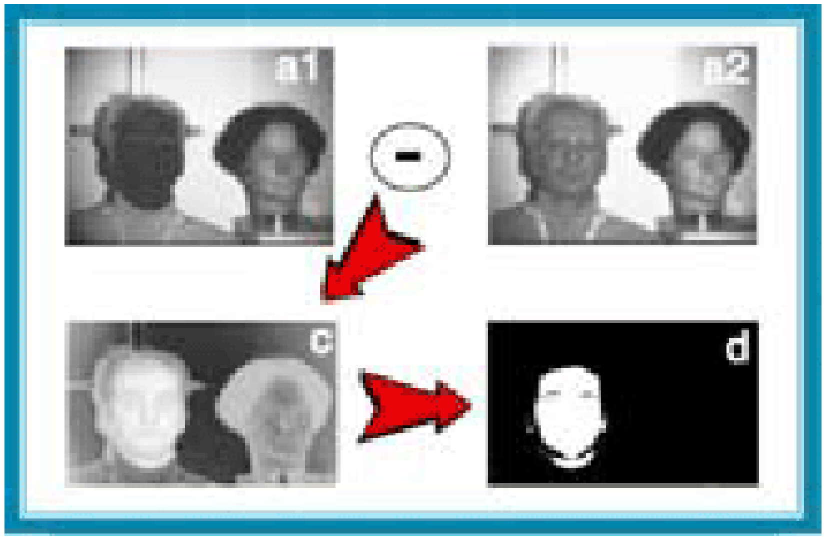


Fig. 12. Caucasian male and a dummy head in the upper band (a1), the lower-band (a2), fusion image (c), and the final thresholded image (d)

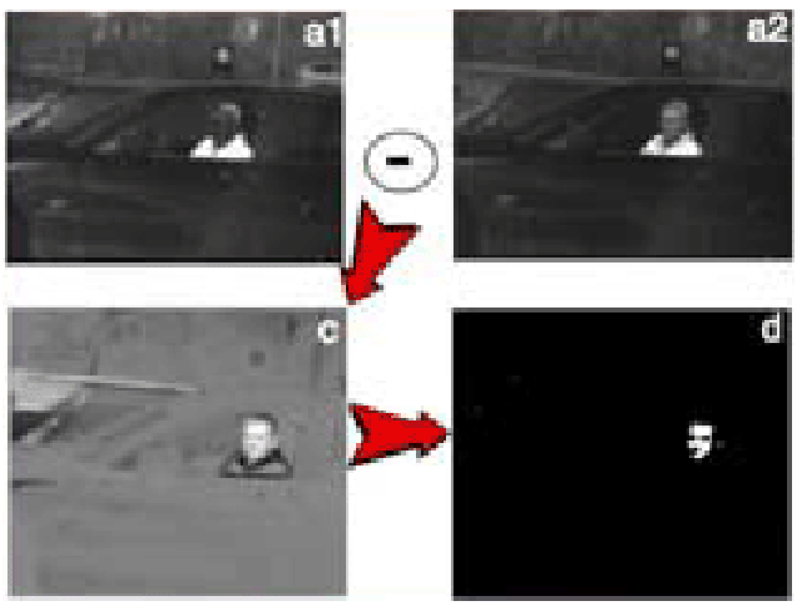


Fig. 13. Caucasian male in a car. The upper band (a1), the lower-band (a2), fusion image (c), and the final thresholded image (d)

true human hair looks different in the upper-band. In figure 14 the upper band shows the skin dark and all own hair, moustache, and eyebrows are white. The dark hair in the middle of the head is a toupee made of human hair. The human hair undergoes a chemical treatment before it can be used in the wigs, which causes the different reflectance in the upper-band.

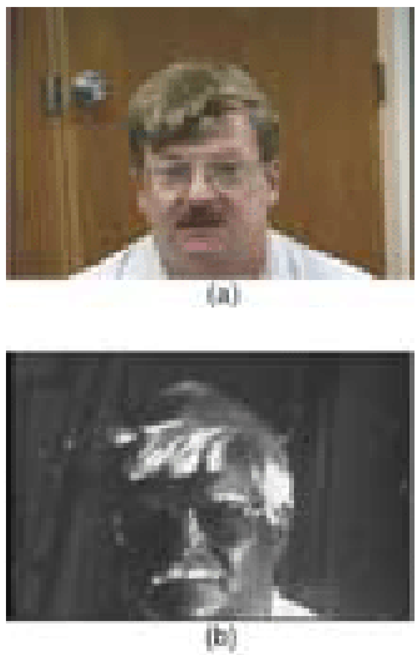


Fig. 14. Caucasian male wearing a human hair toupee. The visible spectrum (a), the upper-band (b)

The researchers are now studying the reflectance properties of all the materials used in professional disguises. They are planning a large study with people wearing disguises.

4 Conclusions

Using infrared in recognition purposes has been studied quite a long but the expensiveness of the required equipments restricts its usage. The method itself seems to be reliable and discriminative enough, especially in controlled environments. When considering the infrared band from biometrics point of view, two quite different subbands can be found. The thermal infrared band is clearly for identification and verification purposes, whereas the near-infrared band suits better for disguise detection and to extract human skin from the background. Thermal images can be used as the ordinary visible spectrum images to get obtain metrics but, in addition, there are also specific methods for thermal images, like elemental shapes. The images in near-infrared band does not picture the heat radiated by the skin. Instead it captures the light reflected by the skin. Therefore it may need artificial illumination to work.

There is not much research done in this area of biometrics but the results show that identification and verification from thermal infrared facial images works better than from visible light images. The researchers suggest that the infrared images could be used as a pre-processing for other methods, for example to pic the faces from the images.

References

1. Biometric identification/authentication techniques. on-line, 2003.
2. Biometrics technologies. Technical report, The Public Safety Wireless Network, January 2003.
3. A. Jain, L. Hong, and S. Pankanti. Biometrics: Promising frontiers for emerging identification market. *??????*, page ?????, 1998.
4. M. Lawlor. Thermal pattern recognition system faces security challenge head on. *SIGNAL Magazine*, November 1997.
5. D. Maltoni, D. Maio, A. Jain, and S. Prabhakar. *Handbook of Fingerprint Recognition*. Springer Verlag, New York, 2003.
6. I. Pavlidis and P. Symosek. The imaging issues in an automatic face/disguise detection system. In *IEEE Workshop on Computer Vision Beyond the Visible Spectrum: Methods and Applications*, pages 15–26, Hilton Head, South Carolina, 2000.
7. F. Prokoski. History, current status, and future of infrared identification. In *IEEE Workshop on Computer Vision Beyond the Visible Spectrum: Methods and Applications*, pages 5–14, Hilton Head, South Carolina, June 2000.
8. P. E. Ross. I can read your face. *Forbes*, 154(14):304–305, December 1994.
9. D. A. Socolinsky, A. Selinger, and J. D. Neuheisel. Face recognition with visible and thermal infrared imagery. *Computer Vision and Image Understanding*, 91(1-2):72–114, July/August 2003.

Table 1. Biometrics comparison. (3:high, 1:low)

Biometrics	Universality	Uniqueness	Permanence	Collectability	Performance	Acceptability	Circumvention
Face	3	1	2	3	1	3	1
Fingerprint	2	3	3	2	3	2	3
Hand Geometry	2	2	2	3	2	2	2
Keystrokes	1	1	1	2	1	2	2
Hand Vein	2	2	2	2	2	2	3
Iris	3	3	3	2	3	1	2
Retinal Scan	3	3	2	1	3	1	3
Signature	1	1	1	3	1	3	1
Voice	2	1	1	2	1	3	1
Facial Thermogram	3	3	1	3	2	3	3

note: high circumvention means that the biometric is difficult to forge