Body Shape-Based Biometric Person Recognition from mmW Images

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Abstract. A growing interest has arisen in the security community for the use of millimeter waves in order to detect weapons and concealed objects. Also, the use of millimetre wave images has been proposed recently for biometric person recognition to overcome certain limitations of images acquired at visible frequencies. This paper proposes a biometric person recognition system based on shape information extracted from millimetre wave images. To this aim, we report experimental results using millimeter wave images with different body shape-based feature approaches: contour coordinates, shape contexts, Fourier descriptors and row and column profiles, using Dynamic Time Warping for matching. Results suggest the potential of performing person recognition through millimetre waves using only shape information, a functionality that could be easily integrated in the security scanners deployed in airports.

Keywords: mmW imaging, body shape information, biometrics, border control security, Dynamic Time Warping

1 Introduction

Millimeter waves are high-frequency electromagnetic waves in the range of $30 - 300$ GHz with wavelengths between 10 to 1 mm, recently found to have interesting properties for various pattern recognition applications. Concretely, imaging using millimetre waves (mmW) has gained the interest of the security community [1–3], mainly due to its low intrusiveness and the ability to pass through clothing and other occlusions.

Traditional applications of this technology include the detection of concealed weapons, explosive and dangerous objects [4]. Millimeter wave scanners have been deployed in several airports such as Los Angeles International Airport or Schiphol Airport, replacing the former X-rays scanners, among other reasons because mmW are not ionizing and therefore less harmful to the health of human beings. The suitability of these frequencies for concealed weapon detection relies on the different signature (due to difference of temperatures) between metallic objects and the human body skin. Automatic detection of dangerous objects and weapons through mmW is still an active research line. Several works have been done in this line using the Quiniti MMW sensor [4, 5].

In the area of biometric person recognition, researchers have commonly proposed the use of images acquired at other spectral ranges: X-ray [6], infrared [7], with the aim

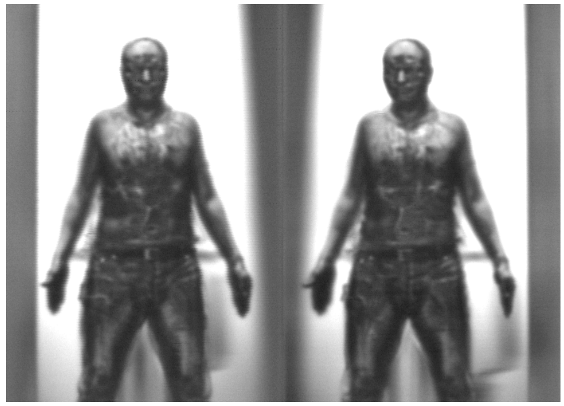

Fig. 1. Pair of millimetre-wave images from the mmW TNO Database. This full scanning image is set in *frontal viewpoint* and *no disguise*.

of overcoming limitations such as illumination variations and body occlusions due to clothing, make up, hair, etc. However, only few works have used mmW images with recognition purposes. This shortage of biometric recognition research based on mmW images is mainly due to the lack of databases of images of people acquired at this band, as a consequence of the privacy concerns of these images [8].

Alefs *et al.* were the first to propose a holistic recognition approach based on the texture information using real mmW images [9]. They exploited the texture information contained in the torso region of the image through multilinear eigenspaces techniques. On the other hand, the works by Moreno-Moreno *et al.* [10] and by Gonzalez-Sosa *et al.* [11] proposed and analyzed a biometric person recognition system based on shape information extracted from synthetic mmW images, exploiting geometrical measures between different silhouette landmarks and features based on contour coordinates, respectively. In all cases, images were extracted in the range of 94 GHz.

Taking into account the interest of the security community in these frequencies and the promising results obtained in the past few works of recognition through mmW [10, 12], one may consider the possibility of using mmW images acquired from the screening scanners simultaneously for detecting hidden objects and performing human recognition. With this approach, the security and recognition control procedures, indispensable for a society threaded constantly, would be enhanced. Body shape mmW information may not substitute primary biometrics such as face, iris or fingerprint, but it may be useful for narrowing the search of possible suspects with very little effort, as a soft biometric [13–15].

Previous works exploiting shape information have been carried out using synthetic images from the BIOGIGA Database [16]. In the present work, we will analyse the discrimination capability of shape-based features using real mmW images from the mmW TNO Database [9]. Table 1 summarizes the key information of the two mmW databases.

Table 1. Existing mmW databases for person recognition purposes

Database	Nature	Mode	Scenarios	Subjects
BIOGIGA [16]	Synthetic simulation	Active and Passive	Outdoors and Indoors	25 male and 25 women
mmW TNO [9]	Real scanner	Passive	Outdoors	50 male

This paper is structured as follows. The real mmW database used in the experiments is explained in Section 2. Section 3 describes the different features and classifier used in the biometric system. The experimental protocol and evaluation of these methods is performed in Section 4 and 5 respectively, and conclusions are finally drawn in Section 6.

2 The mmW TNO Database

The mmW TNO database (created by the Dutch Research Institute TNO in The Hague) is the only database available for research purposes that contains images of subjects extracted in the range of millimeter waves specifically designed for person recognition purposes [9]. Images are recorded using a passive stereo radiometer scanner in an outdoor scenario. The passive millimeter-wave radiation reflected by the subject arrives to a mirror that provides the millimetre-wave passive radiation to two hyperbolic antennas. Fig. 1 shows the result of a full scanning, which is a set of two images with slightly different points of view of size 696×499 (width $\times$ height).

The database is comprised of images belonging to 50 different male subjects in 4 different scenarios. These 4 different scenarios derive from the combination of 2 different viewpoints and 2 different facial configurations. In the first viewpoint configuration, the subject is first asked to stand in front of the scanner with head and arms position at a fixed rack (*frontal viewpoint*). In the second viewpoint configuration (*lateral head viewpoint*), the subject is asked to turned his head leftward while the torso is asked to remain fixed (it may suffer some small changes due to the head movement).

In order to prove the benefits of millimetre-wave imaging above visual imaging, images with different facial configurations were also extracted. In this case, a second round of images with the first and second viewpoint configurations were extracted but now a large part of the facial region was occluded using an artificial beard or balaclava. We will refer to these two different facial clutter configurations as *disguise* and *non disguise*, respectively.

As mentioned before, each scanning is a set of two images. By dividing this set of images into single images o 348×499, the TNO database is comprised of 50 subjects $\times$ 2 viewpoint configurations $\times$ 2 facial clutter configurations $\times$ 2 images per set, making a total of 400 images in the whole TNO database.

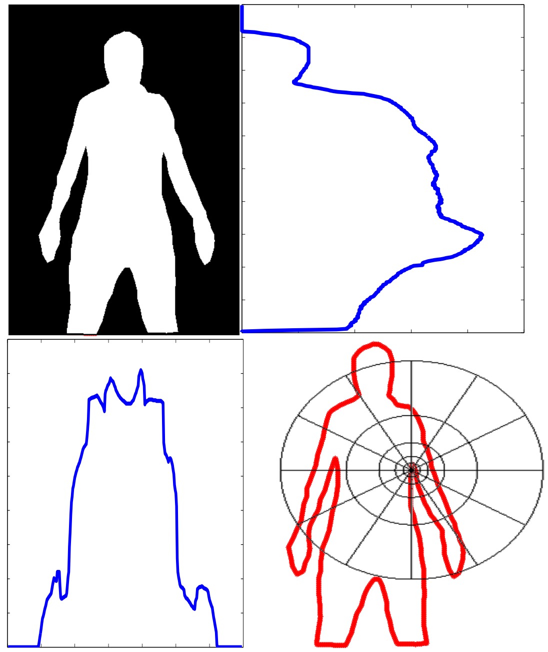

Fig. 2. Body Shape Features proposed in this work to perform person recognition through millimetre wave images. From the binarized image in the upper left corner we compute the sum of foreground pixels at row level (right side), while the sum of foreground pixels at column level is computed from left to right (below). The contour coordinates (lower right corner) is also extracted from the binarized image. The shape context descriptor (log polar histogram) of all contour points is also obtained.

3 System Description

The biometric recognition module of this work aims to perform person recognition through body shape-based information. In this section, details about the different shape features and classifier employed in this work are given. As all the features are shape-based, a segmentation stage is needed. The mmW images of this work have been manually segmented. All the shape features used in this work are extracted from mmW binarized images.

3.1 Shape-based body features

Contour coordinates are used as the baseline feature approach. By coordinate we mean the 2-dimensional vector which specifies the x and y position of every single point within the silhouette of the body. The resolution of the contour is defined by the number of coordinates, being the resolution of the contours extracted from the mmW binarized images of around 2000 points. The starting point of the sequence is the middle point of the head. Fig. 2, on its right lower corner shows an example of the contour coordinates that describe a subject silhouette.

Shape contexts were first introduced by Belongie *et al.* [17]. This technique describes a specific point considering the relative distance and angle of the rest of the points within a shape. This method considers the set of vectors originating from a point to all other sample points on a shape. The number of radial bins (r_bins) and theta bins (θ_bins) are the main parameters of this descriptor. As a result, the shape contexts of a shape with N points forms a vector of size ($N * r\_bins * \theta\_bins$). Note that the log-polar histogram used in this case has a dimension of 12×5 (we decide to use the same configuration of parameters the author originally proposed), where 12 accounts for the number of theta bins and 5 accounts for the number of radial bins (see Fig.2 bottom right). In order to compute the similarity between two shape contexts, different distance methods may be applied.

Row and column profiles Give the binarized mmW image, we compute the sum of foreground pixels at row level from top to bottom (row profile), resulting a 499-vector and the sum of foreground pixels at column level from left to right (column profile), resulting a 398-vector (see Fig. 2).

Fourier descriptors Fourier descriptors [18] are simple to compute and robust against translations and rotations since the effect these transformations cause on the descriptors is completely known. To compute them, first we need to represent the contour coordinates as complex numbers ($u = x + jy$). Secondly, we apply the Fourier transform to these complex numbers to obtain the Fourier descriptor.

3.2 Matching

We have decided to use the Dynamic Time Warping (DTW) distance, which turned out to be better than other distances and classifiers like SVM in previous works [12]. The goal of DTW is to find an elastic match among samples of a pair of sequences that minimize a given distance measure [19]. In this work, DTW is used to obtain a cumulative distance between two sequences of coordinates, which is known to be minimal. Distances are converted into scores through exponential operations, previously normalizing the distance by the number of aligned points between two sequences (k). One of the main advantages of this algorithm is the possibility of dealing with sequences of points that do not have the same dimensionality. In our case, contours from different images do not have the same amount of points.

In the specific case of Fourier descriptors, individual distances are computed independently between row profiles (d_row) and column profiles (d_col). Then, those distances are averaged.

4 Experimental Protocol

The experimental protocol followed in the previous work using the mmW TNO database [9] was very optimistic. It assumed 4 images as input (test images) and 4 images as training. Individual distances were computed comparing pair of images under the same

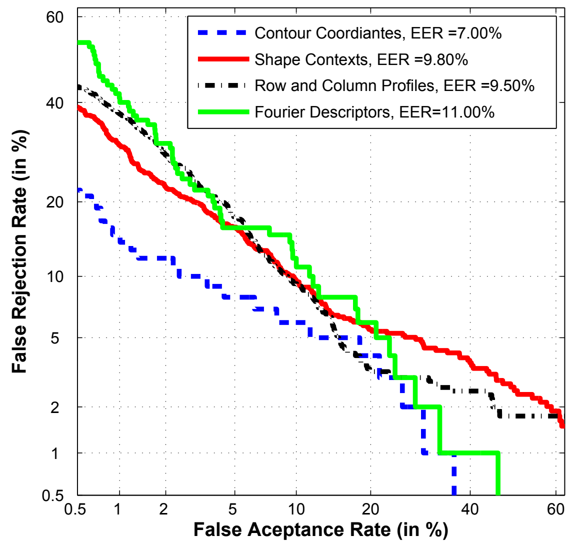

Fig. 3. DET Curves for the biometric recognition system using different shape features extracted from mmW images

viewpoint conditions. Then, the final distance was the minimum over the 4 former individual distances.

The experimental protocol proposed in this work aims to simulate the situation in which a traveller would enter in the mmW scanner deployed in the security area of an airport, hence, using only 1 test image as input. At the same time the subject is being scanned to target concealed weapons or dangerous objects, he is also compared with a previously enrolled image to verify his identity. To simulate that scenario, we use in our experiments the subset of *frontal viewpoint* images of the TNO Database. This subset comprises a total of 200 images (50 subjects $\times$ 1 viewpoint configurations $\times$ 2 facial clutter configurations $\times$ 2 images per set), which are compared one to one.

5 Results

This section describes the experimental work carried out to analyse the performance of the difference body shape approaches described in Section 3. The aforementioned methods are tested with the mmW TNO database in verification mode following the experimental protocol from Section 4.

Fig. 3 presents the DET curves obtained using different body shape-based features approaches. It is clear the superiority of the contour coordinates approach over the other approaches. In terms of EER, the row and column profiles slightly surpass the shape contexts approach. However, at False Acceptance Rate=1%, we have True Positive Rates of 85, 69, 62 and 59% for contour coordinates, shape contexts, row and column profile and Fourier descriptors, respectively. The dimensionality and computational cost of the different approaches vary significantly, being the dimensionality maximum for shape contexts ($N * r\_bins * \theta\_bins = 2000 \times 12 \times 5$) and the minimum for row and column profiles ($348 + 499$).

Fourier descriptors result in the worst performance reaching an EER of 11.00%, which may be due to the unappropriated use of DTW to match this type of features.

It is worth noting that the performance obtained with contour coordinates is improved in the mmW TNO database (7.00%) compared to the 10.00% obtained with BIOGIGA database using a similar experimental protocol. Subjects in the BIOGIGA database were simulated with the arms outstretched in the vertical line between shoulders, whereas the arms position from TNO database is unconstrained. This fact suggest the robustness of contour coordinates over the arm position. However, performance using shape contexts and Fourier descriptors is worsened considerably (from 6.00% and 7.00% in the BIOGIGA database to 9.85% and 11% in the mmW TNO database respectively), which indicates that those descriptors are less suitable for real mmW images.

An additional factor to bear in mind apart from the real/synthetic difference between the TNO and BIOGIGA databases, is the gender difference. The mmW TNO database only contains images from male subjects, while BIOGIGA contains a gender-balanced number of images. This difference in gender may be also affecting the performance of shape features used in this work.

6 Conclusions

The use of millimetre waves radiation has been recently introduced in computer vision applications such as weapons detection or even biometric person recognition applications.

This is the first work addressing the problem of person recognition through body-shape information using real mmW images. The experiments carried out show that person recognition through shape information contained in mmW images is feasible. For future work, texture information will be also considered and analysed, to study the discrimination capability of the whole body mmW signature (shape and texture).

Performing person recognition through mmW images while scanning subjects seeking for hidden objects would provide additional security to border control applications. One may notice however, that the real mmW images used in this work have been extracted using a passive mmW scanner, which obtained good results in outdoor applications where thermal radiation contrast is significant. However, if person recognition is operated inside airports, passive mmW images may not be enough to reach reasonable person recognition rates. Screening scanners actually deployed in airports operate in active mode, that is, artificial illumination is used to produce images with enough resolution to detect weapons and dangerous objects. Hence, more experiments using active mmW images will be needed to gain more insight in this new technology.

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