Public Security Screening for Metallic Objects with Millimetre-wave Images

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ABSTRACT

In this paper we present a system for the automatic detection and tracking of metallic objects concealed on moving people in sequences of millimetre-wave images, which can penetrate clothing, plastics and fabrics. The system employs two distinct stages: detection and tracking. In this paper a single detector, for metallic objects, is presented which utilises a statistical model also developed in this paper. Target tracking is performed using a Particle Filter. Results are presented on real millimetre-wave image test sequences.

1 INTRODUCTION

We present a system for the automatic detection and tracking of metallic objects concealed on moving people in sequences of millimetre-wave (MMW) images, which can penetrate clothing, plastics and fabrics.

MMW imaging is emerging as an important modality for security and surveillance thanks to recent advancements in MMW sensing technology. Providing full monochrome images highlighting concealed threats opens the possibility to analyse shape and locate threats on the body, which is far beyond the reach of conventional metal detection portals. A recently demonstrated proof-of-concept sensor [1] developed by QinetiQ provides video-frame sequences with near-CIF resolution (320×240 pixels) and can image through clothing, plastics and fabrics. The combination of image data and through-clothes imaging offers huge potential for automatic covert detection of weapons concealed on human bodies via image processing techniques. Previous trials of the QinetiQ MMW sensor, involving the Department of Transport and British Airport Authority (BAA), showed potential for passenger screening at airports [2], public event security [1] and detection of illegal passengers in lorries. All trials involved human operators.

The sequences in this paper are generated by an electro-optic sensor working between IR and microwave wavelengths. The sensor forms an image of the temperature received from the scene, which is a standing human subject turning around slowly. Figure 1 shows examples of frames from a typical sequence considered in our work. A person turns around by 360° in front of the sensor and is captured at video rate (12 frames per second). The temperature (and therefore the pixel intensity) is a function of the reflectivity, emissivity and transmissivity of the scene surfaces. At the wavelength used, metallic objects tend to appear bright as they are highly reflective, the human body less bright as it is partially reflective, and clothes partially transparent. An illumination chamber is required for indoor operation [3] but does not expose the subject to harmful radiations.

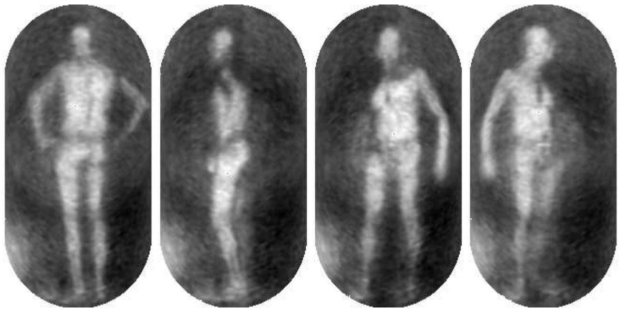

Figure 1: Example MMW image showing a human subject. Notice the Speckle noise pattern particularly apparent on the torso and the substantial smoothing which is applied during the image formation process to minimise visual artifacts.

To our best knowledge, very little work has been reported on the automatic analysis of MMW sequences or images with most authors focusing on very basic segmentation [4, 5] or image fusion [6]. In a related application, shape identification on segmented images [7] has been investigated and suitable shape descriptors proposed. More recently, basic work on object detection has been proposed [8]. The main contribution of our work is therefore to apply advanced image processing techniques to a new video imaging technology of high potential for public security.

This paper is organised as follows: Section 2 presents a statistical mixture model, Section 3 presents work on classifying the millimetre wave images, Section 4 presents work on target tracking and Section 5 presents results on real MMW sequences.

2 MIXTURE MODELS FOR MMW IMAGES

MMW images offer good data for material discrimination as different materials yield, generally speaking, different image properties. We model such differences statistically using a weighted mixture model in which each pdf, f_i, is associated to a specific material:

$$f_{mix} = \sum_{i=1}^{N} \alpha_i f_i(\boldsymbol{\theta}) \qquad (1)$$

where α_i is a weight and $\boldsymbol{\theta}$ a vector of parameters.

To identify the optimal pdf for each material (incl. background, i.e., non-figure pixels), we built a number of mixture models made by combinations of standard distributions (e.g. Gaussian, Rayleigh, Laplacian), optimised the parameters with a standard Maximum Likelihood (ML) algorithm and picked the best fitting combination for the observed image histograms using a Chi-Squared test. We started with background-only sequences (no subject) to identify the background distribution. We then moved to sequences of scenes with a subject but no threats, then with a subject carrying threats (metallic objects). The final result is an optimal mixture model for each material (types of component distributions, and parameters). As an example, Figure 2 shows histograms and results of the ML distribution fit for a scene containing a subject carrying no threats. Here, a two-component mixture model is used: two Gaussians, leading to poor fit, and Laplacian-Rayleigh, showing good fit and little overlap between component distributions.

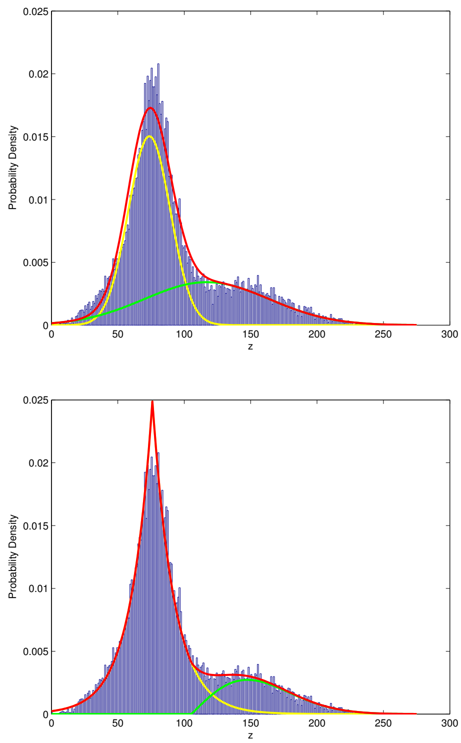

Figure 2: Example of PDF fitting with a subject but no objects in the scene. The top picture shows the output of the ML algorithm for a mixture of two Gaussians while the bottom picture is obtained for a Laplacian and a Rayleigh.

3 CLASSIFICATION OF MMW IMAGES

3.1 Identifying sequences containing threats

The presence of metallic objects changes the maximum temperature recorded significantly, providing a good criterion to identify frames containing threats. Within a sequence, the range of variation of the maximum image temperature provides a reliable measure of the presence of a threat when compared to a normalised threshold. However, detecting which frames in the sequence contain objects is more difficult.

3.2 Identifying frames containing threats

To solve the problem of identifying individual frames containing metallic objects we trained a standard Hidden Markov Model (HMM) to detect significant changes in maximum temperatures (i.e., image intensities). The data is first quantised into 10 levels and the hidden field is composed of 2 states (threat, no threat). A Baum-Welch algorithm [9] is used for parameter estimation, and a Viterbi algorithm to determine the optimal state sequence. As an example, Figure 3 shows the maximum temperature signal for a sequence of 180 frames, and the corresponding frame classification.

3.3 Locating threat regions within frames

We now turn to the problem of locating the image region corresponding to a metallic object in frames classified as containing threats. We use Expectation Maximisation (EM) to perform the necessary unsupervised clustering. The EM algorithm uses ML to recompute the pdf parameters until a convergence criterion is met. We initialise the mixture model to the one containing the optimal distributions for the background-body-metal case (as defined in Section 2) with default parameters. Notice that this is not necessary for the EM algorithm, but improves the convergence speed significantly. An example of threat location is shown in Figure 4, where the estimated threat region is highlighted in white.

4 TRACKING THREAT REGIONS

The results of the classification stage applied to sequences of persons carrying metallic threats is

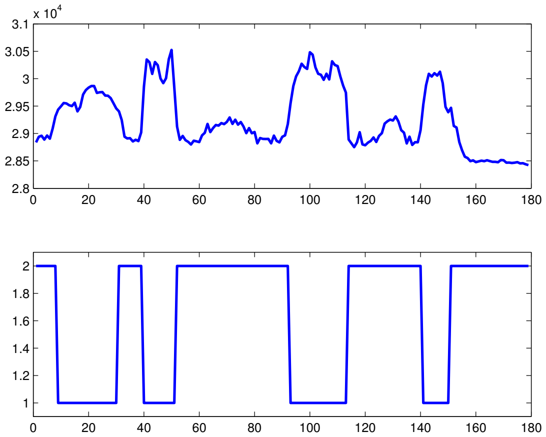

Figure 3: An example of the HMM model being applied to a sequence of 180 frames. In the top row the maximum image intensity is shown for each frame in the sequence. In the bottom row the HMM state (1=object present, 2=no object) is shown across the sequence.

Figure 4: Expectation-Maximisation segmentation (right) of a scene containing a potential target in a MMW image (left).

twofold: a set of frames showing metal threats, plus, in each such frame, the regions corresponding to threats. Such regions are characterised by frame number, centroid, and area. The problem is now to track such regions throughout a sequence for as long as the region remains visible, with birth, death and temporary occlusion common. The problem is made more difficult by the noisy nature of the MMW images making accurate segmentation difficult.

Tracking objects in visible-wavelength sequences is a well-studied problem in image processing and computer vision [10]. Particle filters (PF) [11] are a powerful class of algorithms removing the Gaussian-distribution constraint typical of Kalman filters. They also provide robustness against clutter, a significant problem in MMW images given the noise characteristics. A common problem with PF is the *degeneracy problem* where after several iterations all but a few particles have negligible weights. For this

Table 1: Test Sequences Employed

Sequence	Frames	Threat	No. Threat Frames
Plain01	211	No	—
Plain02	252	No	—
Plain03	218	No	—
Plain04	236	No	—
Threat01	242	Yes	24
Threat02	155	Yes	27
Threat03	179	Yes	56
Threat04	136	Yes	30
Total	1629	4/8	137

Table 2: Threat Identification

Sequence	Threat?	$Error$	E_{false}	E_{miss}
Plain01	No	—	—	—
Plain02	No	—	—	—
Plain03	No	—	—	—
Plain04	No	—	—	—
Threat01	Yes	8%	0%	100%
Threat02	Yes	3%	0%	100%
Threat03	Yes	5%	22%	78%
Threat04	Yes	8%	0%	100%

reason we chose to employ a Regularised PF (RPF) [11] which has an improved re-sampling stage, helping to avoid the degeneracy problem.

The tracking filter was employed with a state vector containing the position, velocity and area of the target: $(x, \dot{x}, y, \dot{y}, \phi)^T$. Suitable values for the prediction and observation covariance matrices were determined empirically. Due to the nature of the segmentation, it is necessary to allow greater variance within the area measurements than for the position estimate.

5 EXPERIMENTAL RESULTS

To evaluate our system, eight test sequences were employed, four with subjects without a threat and four with subjects carrying a threat, giving a total of 1629 frames and including 137 frames where a threat is visible. Table 1 summarises the details of the test sequences.

Table 2 shows the results of the sequence and frame threat identification algorithms described in Subsections 3.1 and 3.2, giving percentage error in classified frames ($Error$) with a breakdown of target frames missed (E_{miss}) compared to false alarms (E_{false}). The results clearly show that both stages of the threat identification perform very effectively. The missed target frames was primarily in situations where the target was identified through shape rather than intensity.

Finally Table 3 shows results for the EM classification and RPF target tracking, giving the average

Table 3: Target Tracking

Sequence	Average Targets	RMSE
Threat01	2.4	8.07
Threat02	2.1	11.61
Threat03	1.3	5.05
Threat04	1.1	5.46

number of targets (true target + clutter) per frame for the sequence and RMSE of the tracked position. The ground truth for the target position was manually tracked and is accurate to ± 2 pixel.s It can clearly be seen that excellent target tracking results have been achieved, even in the sequences with considerable clutter (Threat01, Threat02). The comparatively poorer tracking results seen in Threat02 are due to the very short time span over which the threat is visible (approx. 9 frames on each occassion compared to an average of 15 frames for other sequences). In this instance, the particle filter does not have enough time to converge.

6 CONCLUSIONS

We have presented a novel system for the automatic detection and tracking of metallic objects concealed under clothes using MMW sequences. The recent emergence of MMW video sensors makes our work very timely. To the best of our knowledge, no previous system combining MMW video imaging and advanced image processing techniques has been reported to date. Results have proven reliable on the current data test set. Future work will extend our approach to a wider range of materials, more complex tracking scenarios, and incorporating human body models to improve tracking and provide 3-D visualisation preserving privacy.

Acknowledgements

We would like to thank Beatriz Grafulla González and QinetiQ for providing the data sequences and for technical discussions. This work is supported by EPSRC Research Grant GRS/68088 “ATRIUM” (Automatic Threat Recognition and Identification Using MMW).

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