A CLASSIFIER BASED APPROACH FOR THE DETECTION OF POTENTIAL THREATS IN CT BASED BAGGAGE SCREENING

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ABSTRACT

Recent years have seen increased use of Computed Tomography (CT) based Unaccompanied Baggage and Package Screening (UBPS) systems for luggage examination to ensure air travel security. In this paper we present a research work on developing a system for automatic detection of potential threat items in cluttered 3D CT imagery originating from UBPS systems by combining 3D medical image segmentation techniques with 3D shape classification and retrieval methods.

Index Terms— Aviation security, 3D medical image segmentation, 3D Zernike descriptors, histogram of shape index, support vector machine.

1. INTRODUCTION

In recent times, air travel security has become of significant concern. Advanced security screening systems are becoming increasingly used to aid airport screeners in detecting potential threat items [1].
Although several X-ray technology based automatic systems exist for threats detection [2], only a few of these systems make use of the well established pattern recognition and machine learning techniques [3, 4, 5, 6]. In addition, the proposed systems are designed for 2D X-ray images and do not take advantage of using information offered by more recent systems using 3D CT imagery. In practice, 2D X-ray images obtained from the current luggage screening systems are not able to unambiguously reveal exact luggage content and hence make the process of screener interpretation of 2D X-ray images a difficult task - particularly for cluttered luggage. As such, the need to use the available 3D CT data is of great importance to enhance such screening procedures as it allows the screener to access to information which is not available in 2D X-ray to provide improved viewing and interpretation.

In this paper we propose a new method for threat detection which deals, in contrast to the state-of-the-art, with 3D volumes originated from CT based UBPS systems. In addition, it differs in two important aspects. First, the integration of CT medical image segmentation tools in the process of identifying threat items. Although image segmentation is already an established tool both in the field of exploratory medical research and in routine daily clinical practice, such techniques have not been used in the context of screening systems and the associated cluttered baggage imagery. Second, since 3D CT imagery is considered in our work, 3D shape descriptors developed within the established content based 3D shape recognition and retrieval systems are explored and used within a classifier based approach for threat item identification. The proposed classifier is tested using a linear Support Vector Machine (SVM) learning algorithm and two popular 3D shape descriptors (3D Zernike descriptors [7] and histogram of shape index [8]).
This work is conducted as part of a larger project which aims to investigate the use of medical image segmentation, volume based shape recognition, and classification techniques for integration into existing CT based UBPS procedures.

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2. OVERVIEW OF OUR APPROACH

Figure 1 shows the overall framework of our approach. The system mainly contains two modules, one for training and one for classification following the traditional data-driven machine learning approach.

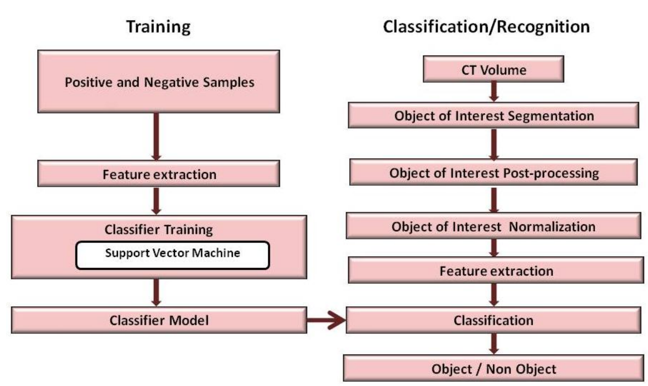

Fig. 1. Outline of our system.

In the training module, the system takes as input pre-segmented 3D threat and non-threat objects (positive and negative 3D samples). These samples are extracted from CT volumes which are obtained by the conventional CT process of stacking multiple 2D X-ray slices registered along the third dimension. All these samples are preprocessed, normalized and for each 3D example a feature vector representation is constructed (positive and negative samples). This yields a set of positive and negative feature vectors that are then fed into the SVM based classification algorithm to train the classifier to differentiate between different classes.

In the testing module, new unseen cluttered CT volumes originating from UBPS systems are used. The system segments the 3D objects to be identified and performs post-processing and normalization on each object. A feature vector is then extracted from each segmented objects as in the training step and feed into the trained SVM classifier to determine the class of the object (threat object or non threat).

2.1. Object of Interest Segmentation

During training and classification phases, an initial segmentation stage is required to separate the objects of interest from the rest of cluttered luggage content. In our work, we have used a technique from the well established field of medical image segmentation where several methods have been proposed which can be broadly classified into two categories. Region-based methods which perform the segmentation by finding coherent regions according to some criteria, and boundaries-based methods that find the boundaries of the object of interest [9].

In our work, we have tested several methods from each class including region growing, fuzzy connectedness, watershed, level sets and threshold based methods [9]. We selected fuzzy connectedness [10] as an initial segmentation method as it outperforms the other segmentation methods in our cluttered baggage data, especially for thin objects such as weaponry.

2.2. Feature vector

As in this work volume data is processed rather than 2D images, the 3D segmented objects are described by a 3D shape descriptor. To identify a suitable descriptor we refer to the most popular 3D shape descriptors used for 3D shape recognition and retrieval [11, 12]. Following the review of [11, 12], we select two appropriate 3D shape descriptors for our current work: rotational-invariant 3D Zernike descriptors [7] and histogram of shape index [8]. These descriptors have proven to uniquely characterize object shape [7, 8]. Both descriptors are global features which describe global properties of the 3D object shape by some finite-dimensional vector of real values. 3D Zernike descriptors are obtained from a voxelized model of 3D objects and are rotation invariant by design. In comparison to many other 3D shape descriptors, 3D Zernike descriptors are robust to noise [7]. Histogram of shape index is a local surface shape measure based on the curvature of the object. It is constructed by segmenting the range of the shape index curvature measure into equal sized histogram bins. The shape index represents the shape of a local surface by a single-value angular measure. It is defined as follows:

$$SI(p) = \frac{1}{2} - \frac{1}{\pi}.tan^{-1}\frac{k_1(p) + k_2(p)}{k_1(p) - k_2(p)} \tag{1}$$

Where $k_1(p)$ and $k_2(p)$ are the maximum and minimum curvature at point p of the surface. Each value of the shape index, which is in the range [0,1], corresponds to a distinct surface shape except for an exact plane where it is undefined. In contrast to 3D Zernike descriptors, the shape index is derived from a surface mesh model [8].

2.3. Object of Interest Preprocessing and Normalization

As with most of shape representation methods, 3D Zernike descriptors and histogram of shape index require pose normalization step in which the 3D object is normalized to achieve invariance with respect to geometrical transformations (i.e. rotation, scale, and translation). 3D Zernike descriptors are rotation invariant but do not have scale and translation invariance properties. The histogram of shape index descriptor is rotation and translation invariant. Therefore, our 3D objects are pose-normalized with respect to scale and translation for 3D Zernike descriptors calculation and are scale normalized for the histogram of shape index calculation. Scale and translation invariance are achieved using the following basic procedure:

1. Starting from a CT volume containing a segmented object of interest, a bounding box that encloses this object is computed.

2. The region around this object is cropped based on its bounding box. The result volume contain only the segmented object.

3. The cropped volume is then resampled at the specified scale.

In addition, since extracted objects from earlier segmentation are often disconnected, they are first preprocessed using a 3D morphology dilation filter.

3. EXPERIMENTS AND RESULTS

Our evaluation experiments are based on a CT based UBPS database we have built which contains two threat object classes: guns, and bottles. Within current air travel security regulations, bottles represent interesting target objects to examine in any luggage screening process. The number of scans within this dataset is 236. These scans include luggage that have threat items and luggage that do not have threat items.

Sets of 7 different guns and 35 bottles are used. Therefore we have used the bottle class to test our system since the current available gun class is very small.

In our experiments, we compare the performance of our system in identifying bottles on the above constructed database using Zernike descriptors, histogram of shape index and both combined.

To generate Zernike descriptors, we have used maximal order of 20. This yields to a 121-D Zernike descriptors feature vector. The step bin of the shape index used to compute the histogram is 0.005 and since the shape index values are in the range [0,1] the result histogram has a size of 200. Therefore, the total length of the combined feature vector obtained by concatenating Zernike descriptors and histogram of the shape index is 321 features.

The training set used in our experiments consists of 24 bottle volumes (positive samples) and 55 non-bottle volumes (negative samples). The set of bottles have been segmented and normalized to a scale of 60x60x60 voxels. Some bottles have been represented more than once as they are originated from different scans. In Figure 2 we present a representative set of the positive samples used in our experiment. Negative samples are randomly generated from negative CT volumes (without bottles). These samples have been normalized to the same size used for positive samples.

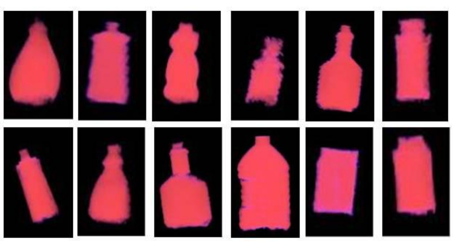

Fig. 2. A representative set of 3D positive samples used in our database.

The test data set consists of 61 positive samples originating from CT scans different from those used in training stage and 65 negative samples. Among the positive samples set, 19 bottles have not been used in the training set.

In Table 1 we summarize the experiments via accuracy, precision, true negative rate (TNR) and recall measures. It can be seen that our method achieves very good results in particular for the histogram of shape index when there are only two missed detections. Additionally, as the combined feature vector achieves the same results as the histogram of shape index, we conclude that when 3D Zernike descriptors are combined with the histogram of shape index, the classification results are only decided by the histogram of shape index which overcomes 3D Zernike descriptors.

Some representative detection results obtained by our system using both feature vectors are depicted in Figure 3. It can be seen that bottles are detected independently of their segmentation quality. The later depends on the bottle background in the bag which contain usually significant amount of clutter and exhibit a huge variability among different bags. In addition, the segmentation results depend on how much the bottle is filled. Indeed, the region segmented by our method is the bottle content (liquid). When a bottle is not full, the shape of the liquid inside the bottle takes several CT forms depending on the position of the bottle in the bag and also the position of the bag on the conveyor. This explains in part why segmentation results of the same bottle are slightly different when placed in different bags, in addition to the clutter of the bag and the bottle background (e.g. Figure 4). This is a synonym to the 3D occlusion case in non-CT based 3D object retrieval. Using our method as shown in Figure 3, bottles that are not completely full are still detected.

Type of feature vector	Accuracy	Precision	TNR	Recall
3D Zernike descriptors	93.65%	88.52%	90.14%	98.18%
Histogram of shape index	98.41%	96.72%	97.01%	100%
Zernike descriptors and Histogram of shape index	98.41%	96.72%	97.01%	100%

Table 1. Detection performance of our method

The segmentation of the bottle contour is a difficult task. Medical imaging segmentation methods are not suitable for this purpose since the specification of the initial seed region necessary to perform the segmentation is very difficult.

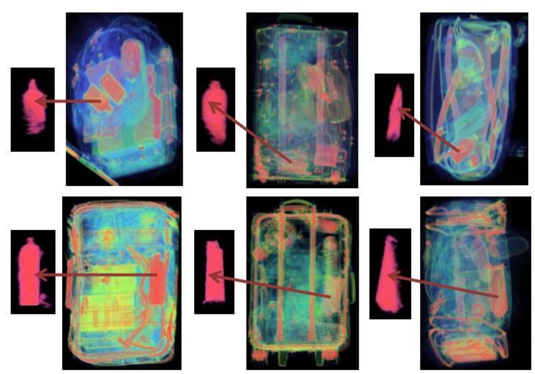

Fig. 3. Examples of detection results (bottles classified correctly) obtained by our detector.

Figure 5 shows some missed detections made by our method when Zernike descriptors is used as a feature vector. Though all the bottles which are not detected are the same used in training stage, they have not been recognized in the testing step. This confirms that even when a bottle is used in train-

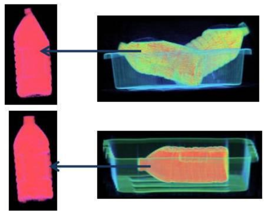

Fig. 4. Difference in segmentation results of the same bottle.

ing, once it is placed in another cluttered bag, it may not be detected due to the aforementioned factors that affect segmentation results. However, all the 19 bottles which have not been used in training have been correctly detected using the two types of feature vector as well as their combination.

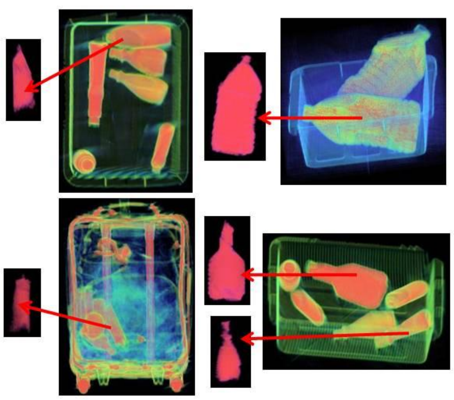

Fig. 5. Examples of errors (missed detections) made by our method when 3D Zernike descriptors are used as a feature vector. The Figure shows the original bags and the missed segmented bottles.

4. CONCLUSION

In this paper we have proposed a new method for the detection of potential threats in 3D volumes originated from CT based UBPS systems. The proposed method incorporates techniques from the fields of medical image segmentation and shape recognition and retrieval. The method which is a SVM classifier based approach was tested using two popular 3D shape descriptors: 3D Zernike descriptors and histogram of shape index. The obtained results are very encouraging and show that our method works very well on our currently UBPS dataset. In particular, we have found that histogram of shape index performs much better than 3D Zernike descriptors.
Due to the limitation of the available dataset, the method was tested only on the detection of bottles. The application of our method to the detection of more sophisticated threat objects such as weapons is an interesting future extension.

5. REFERENCES

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