

INVESTIGATION OF A CLASSIFICATION-BASED TECHNIQUE TO DETECT ILLICIT OBJECTS FOR AVIATION SECURITY

Steve Green, Michael Blumenstein, Vallipuram Muthukumarasamy and Jun Jo
School of Information Technology,
Griffith University, Gold Coast Campus, QLD 9726, Australia.
Email: {s.green, m.blumenstein, v.muthu, j.jo}@griffith.edu.au

ABSTRACT

In this paper we present an initial investigation into the use of a classification-based technique for illicit object detection in aviation security. Current threats in aviation security are becoming more sophisticated in that it is extremely difficult to detect possible threats of terrorism without severely hindering passenger life style. In order to provide adequate security, previous work by the authors has proposed an intelligent security technology framework to provide the civil aviation authority with maximum security whilst minimising adverse impacts on airlines and airport operations. In this work, the feasibility of employing a classification-based technique is investigated for the purpose of identifying illicit material in hand luggage. In this research, a neural network trained with backpropagation is used in conjunction with a newly proposed feature extraction technique for classifying various object images. Encouraging results are reported that may facilitate future, automated hand luggage scanning.

KEY WORDS

Object detection, aviation security, neural networks

1. Introduction

The problem of computer-aided screening of hand luggage at airports and other entry points is fast becoming a topic of great importance with regards to homeland security [1]. Recent terrorist activities have lead to added congestion in airport terminals, delays, inconvenience, more restrictions on carry-on luggage, a sense of anxiety, and sometimes a breach of privacy amongst the public. All the above factors have added to the cost of air-travel and have impacts on socio-economic factors.

To combat threats to aircraft and to the public, hundreds of flights have been recalled to terminals after being air-born, there have been numerous occasions of evacuations, passengers rechecked, or even asked to perform strip searches [2].

All these extra measures attempt to give a sense of security to the public and to build confidence that air-travel is now safe. However, security experts know too well that the current measures are far from adequate to

prevent any possible future terrorist threats [3]. The reality is that more than 1 billion suitcases, an average of 3.8 million daily, will have to be scanned in the USA alone [3]. The latest and fastest "InVision" technology can scan approximately 128–542 bags/hour - roughly two paneloads per hour [4].

The responsibility for checking is heavily reliant on the capability of the scanning machines and the skills of the operating personnel. Most scanners were originally designed for detecting specific items such as explosives, contra-band, and metals to satisfy security and customs needs. Modern security threats can easily escape the scanners, mainly due to the lack of detection ability and the inability to easily incorporate any additional security information into the detection mechanism.

This paper describes the classification phase in an automated system for the detection of illicit objects in hand luggage [5]. Results for the recognition of various objects from grey-scale images is presented, based on a newly proposed feature extraction technique and a neural network classifier. Results are compared with an established feature extraction technique providing encouraging results.

2. Computer-Aided Screening (CAS)

Any security screening solution, either passenger or luggage inspection, needs to satisfy a number of very stringent criteria, including:

- (i) a very high level of accuracy
- (ii) reasonably fast operation and
- (iii) acceptability with the public

Conventional X-ray screening systems at airports measure attenuated X-ray energy after it passes through a scanning object. Using high-resolution grey scale images, the security operator can identify weapons and contraband items, with a prior knowledge of characteristic shapes [6][7]. New X-ray imaging systems at airports use dual-energy analysis to estimate the atomic numbers of materials in the passenger baggage [1][8]. This method obtains a measure of the density and thickness of the material. Several approaches have been proposed, such as transmission scattering and computer tomography, to

separate objects in complex images so that an automated Explosives Detection System (EDS) can be developed [9]. Advanced X-ray luggage inspection systems are based on scattered X-ray energy imaging techniques, which gives better results, particularly in detecting plastic explosives [10].

Substantial improvements are required in existing techniques to meet the current security needs [3][9] – a more reliable detection mechanism, with low false positives, at an acceptable speed is a real research challenge. Some of the proposed solutions to achieve more reliable detection require enormous computational overhead [11][12]. Those techniques try to reconstruct a more precise 3D object using computed tomography (CT) 3D information [9][11]. Although application of 3D imaging is currently being widely used in the medical and environment industry, only recently has 3D imaging been applied to X-ray machines for aviation security.

Any analysis of the procedures involved in digital X-ray screening technology may be classified into 3 main parts: segmentation, feature extraction, and classification.

2.1 Segmentation

In order to determine whether an object is threatening or not, it is first necessary to separate it from its surroundings (i.e. a background or other objects). It is for this purpose that image segmentation is utilised. A number of segmentation techniques have been employed for explosives detection including grey-level thresholding [13] region growing [7] and probabilistic relaxation labelling [1][13]. Many of these techniques have been developed and widely tested in other areas such as medical applications. It must be noted that effective segmentation significantly depends on the type of application being considered.

2.2 Feature Extraction

When the object or region of interest (ROI) is identified in the whole image, features need to be extracted from the segmented objects. Important features that have been identified for illicit object detection include edges, shapes and texture features [1]. Feature extraction is more complicated when the image has overlapping objects. However, this problem can be addressed earlier in the detection process during segmentation. Although feature extraction has been studied well for other applications, more significant features need to be identified for efficient detection of illicit materials [14].

2.3 Classification

Once significant features are extracted from X-ray images, a good classification technique is needed to identify the target object with a quantified confidence

level so that this information can assist the security operator in making an appropriate response. Classifiers ranging from Artificial Neural Networks (ANNs) to the discrete cosine transform are used for image classification, shape recognition, and image retrieval. A number of linear classification methods have been applied to illicit object detection [1], whereas ANNs have only been used in a limited capacity [15]. Currently, the classification rate in x-ray luggage scanning is still well below satisfactory levels. The investigators' experience shows that ANNs can be very effectively used for feature extraction and classification in general [16][17].

2.4 Problems with Existing Techniques

Research into the development of accurate CAS systems is important for the future of security screening. The main areas where computing technology may be applied is for the (i) automated detection of dangerous explosives and concealed weapons i.e. segmenting objects of interest, feature extraction and classification and (ii) the integration of current qualitative/quantitative security intelligence to assist in the detection process. Although systems exist that analyse spectra from neutron-based techniques for explosives detection, there is a distinct lack of research in combining multiple features and classifiers for recognising illicit material in x-ray images. A thorough investigation of these techniques would be beneficial for the overall object detection problem in x-ray images and could potentially contribute to an increase in speed, a decrease of false alarms and increased assistance to human screening operators.

In the following sections, an overview of a newly proposed, automated object detection system will be provided. Following this, a detailed description of the classification-based component of the system will be presented.

3. System Overview

This research describes an intelligent task-oriented object detection system model, which is an image-based, computer aided screening system for inspecting hand-luggage to provide the civil aviation authority with maximum security while minimising the adverse impact on airlines and airport operations.

The proposed system uses a classification-based strategy, which searches a processed, grey-scale hand luggage image using a fixed/variable-sized window to scan the image in a raster format. This is similar to the technique described in [18]. The sub-images extracted by the window search are then processed to determine whether an illicit object has been found. Each sub-image is processed by being passed to an edge detector, feature extractors and finally a neural-based classifier. The entire system is presented in Figure 1.

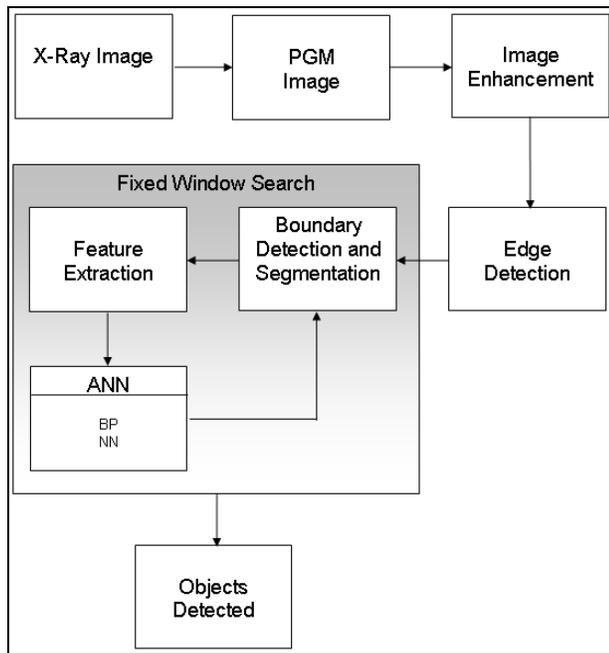


Figure 1: System Overview – Image Processing, Feature Extraction and Object Detection

3.1 Pre-processing and Edge Detection

Pre-processing of images can be used to improve the success of further processing steps such as feature extraction and classification. Some simple techniques involve using convolution to enhance or smooth images before applying edge detection algorithms. In the current system, no pre-processing was used on the images before applying the Prewitt edge detection algorithm [19]. After determining the edges of the image, unwanted noise and outer white space was removed (see Figures 2 and 4). Unwanted noise was removed from images by specifying a window size and moving it through the image. If pixels inside a particular window were not touching the window's edge (connected component), those pixels were removed. Once the image was processed, feature extraction algorithms could be applied to extract input values for the neural network.



Figure 2: Before and after noise reduction following the edge detection process.

3.2 Feature Extraction

In this section, the two feature extraction techniques used in this investigation are described, the density feature and the modified direction feature (MDF).

3.2.1 Density Feature

The density feature extraction technique describes the local concentrations of foreground pixels in each image, providing a simplified representation of their distribution [20]. Following edge detection, the density feature extractor breaks an image down into small windows of equal size and analyses the density of black and white pixels, providing the classifier (ANN) with floating point inputs. To obtain these floating point values, the number of foreground pixels contained in a particular window is tallied and divided by the total area of the window. Hence, for a window that is 5x5 in dimension, containing 6 foreground pixels, the Density value would be 0.24 as specified by: $NumberOfForegroundPixels/WindowArea$ (i.e. 6/25). Once all density values were obtained, they were assembled into an input feature vector and accompanied by a desired value (for classifier training).

3.2.2 Modified Direction Feature (MDF)

MDF has been detailed elsewhere [21] and will only be briefly described here. MDF feature vector creation is based on the location of transitions from background to foreground pixels in the vertical and horizontal directions of an image represented by edges. When a transition is located, two values are stored: the Location of the Transition (LT) and the Direction Transition (DT) (see Figure 3). An LT is calculated by taking the ratio between the position where a transition occurs and the distance across the entire image in a particular direction. The DT value at a particular location is also stored.

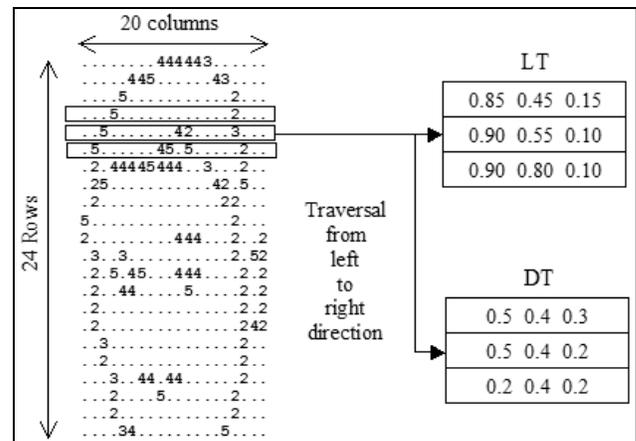


Figure 3: Processing LT and DT values from the left-to-right direction

The DT is calculated by examining the stroke direction of an object's boundary at the position where a transition occurs (as defined in Blumenstein *et al.* [22]). Finally, a vector comprising the [LT, DT] values in each of four possible traversal directions is created. The complete algorithm for the calculation of location transitions and direction transitions is shown below.

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For each direction of traversal
  For i = 0 to number of lines
    For j = 0 to number of transitions
      IF traversal from left to right THEN
         $LT = 1 - v / \text{object width}$ 
      ELSE IF traversal from top to bottom THEN
         $LT = 1 - v / \text{object height}$ 
      ELSE IF traversal from right to left THEN
         $LT = v / \text{object width}$ 
      ELSE IF traversal from bottom to top THEN
         $LT = v / \text{object height}$ 
      END IF
       $DT_{(v)} = dv / 10$ 
      Record [LT,  $DT_{(v)}$ ] as a feature pair in
      feature vectors
    END For
  END For
END For

```

In the MDF algorithm above, a line of traversal refers to a row or a column in a 2D binary image. LT is the value of the transition value and $DT_{(v)}$ is the value of the direction feature at the position where a transition occurs. When a background to foreground pixel transition occurs, the exact location of the transition is represented by v , and the direction number at the position of transition is denoted by dv .

3.3 Neural Network-based Classifier

In this research, the ANN that was adopted for the process of classifying objects into illicit and non-threatening object categories was a fully interconnected, feedforward ANN. The network was trained using the backpropagation (BP) algorithm. In the experiments conducted, the BP-ANN was trained with images processed by density and MDF extraction techniques.

For the density feature extraction technique, the number of inputs was 100, whereas MDF generated a feature vector of 120 inputs. The number of hidden units of the network was varied experimentally and the number of outputs remained constant at three, each one representing an image class. The first output represented an illicit object class, whereas the last two represented non-threatening object classes (further described in Section 4.1). Figure 4 displays the ANN model.

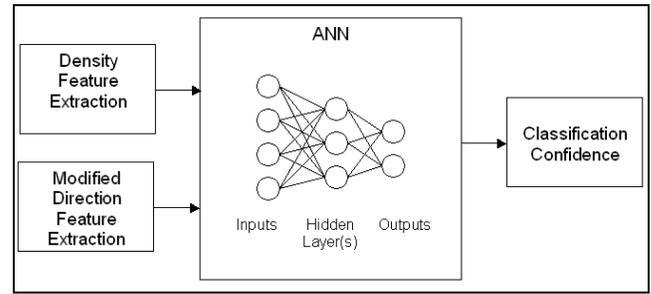


Figure 4: ANN model

4. Results

4.1 Image database

To test the classification scheme based on the MDF and density feature extraction techniques, a small database was created including illicit and non-threatening objects. To represent threatening objects, various gun images were compiled whilst the remainder of the data was comprised of non-threatening objects of two specific types: bottles and faces. The choice of these non-threatening objects was dictated by the ease of their acquisition.

The bottles face and guns (BFG) image database consists of 1013 grey scale images of varying sizes. It is divided into two sets, a training set and a test set. The training set consists of 600 images (200 of each type), where minimum and maximum image sizes are 56×200 and 727×1130 respectively. The test set consists of 413 (138 bottles, 132 faces, and 143 gun) images, where minimum and maximum image sizes are 49×200 and 1142×674 respectively. All face images were taken from the FERET face database [23]. The bottles and guns were gathered from a custom database.



Figure 5: Sample images of illicit and non-illicit objects before and after edge detection (not to scale)

4.2 Classification results

In this section, results for the classification of illicit objects are presented in tabular form. Table 1 presents the results obtained when the density feature extraction technique was used to process images, and Table 2

provides results when using MDF. In both tables, top results for three hidden unit configurations are presented, using two noise reduction window sizes.

The test set classification rate was calculated based upon the number of successfully recognised illicit objects (true positives). Also listed below are the numbers of non-threatening items incorrectly labelled as illicit objects (false positives).

Table 1: BP-ANN classification rates using the density feature extraction technique

Noise Reduction Size	Illicit object classification rate [%] True positive/False positive					
	# Hidden Units					
	10		20		24	
10x10	91	10	96	8	95	6
15x15	91	0	92	4	90	9
20x20	94	10	94	7	96	6

Table 2: BP-ANN classification rates using the MDF extraction technique

Noise Reduction Size	Illicit object classification rate [%] True positive/False positive					
	# Hidden Units					
	10		20		24	
10x10	93	3	97	2	97	1
15x15	91	0	94	3	98	1
20x20	96	1	95	2	96	3

4.3 Discussion

As may be seen from the tables above, the best result (a classification rate of 98%) was obtained using MDF extraction with a noise reduction window size of 15x15 and an ANN with 24 hidden units. In this case, the false positive rate is only 1%. The best result obtained with the density feature was 96%, with a noise reduction of 20x20 pixels, a neural network of 24 hidden units, and a false positive rate of 6%.

Overall, MDF provided a better classification rate when higher settings were used for the number of hidden units and a 'medium' window size for noise reduction. The density feature performed best with a higher number of hidden units and a larger window size for noise reduction.

5. Conclusions and Future Research

National security has become one of the foremost issues of concern that needs to be thoroughly addressed by every nation, in particular the developed nations, which are playing an active role in counter terrorism. One of the areas seriously affected is that of airline security, specifically the process of inspecting carry-on baggage. Recently, research has more urgently been directed towards the detection of illicit materials such as explosives and concealed weapons in passenger luggage.

The main objective has been to provide the maximum security while minimising the adverse impact of operations at airports.

In this paper, we have described an intelligent illicit object detection model, which incorporates an ANN-based classification system for the detection process. At this stage, features extracted are not invariant to object rotation. Future research will need to address this point. Early results are encouraging for classifying threatening and non-threatening objects from a database of distinct images using a newly proposed feature extraction technique.

Future research will see the use of a second classifier for texture recognition, which will be fused with the BP-ANN described in this paper along with additional intelligence information. The MDF extraction technique will also be extended to deal with more difficult images containing significantly rotated objects. Finally, the resulting classifiers will be incorporated into the object detection system for testing on real-world luggage images.

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