

# INTELLIGENT ILLICIT OBJECT DETECTION SYSTEM FOR ENHANCED AVIATION SECURITY

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## ABSTRACT

Although aviation security is not a new phenomenon to the world, current threats are much more sophisticated such that it is extremely difficult to detect possible threats of terrorism without severely hindering passenger life style. In order to provide adequate security, a much more sophisticated, reliable, and fast screening technique is needed for passenger identification and baggage examination. In this paper we have proposed an intelligent security technology system that provides the civil aviation authority with maximum security whilst minimising adverse impacts on airlines and airport operations. The proposed system uses appropriate image processing techniques, feature extraction and artificial neural networks for detecting illicit objects in hand luggage.

## 1. INTRODUCTION

Increased security in the aftermath of the 9/11 attack in the United States of America has 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 these simply add cost to air-travel and thus have an impact on socio-economic factors.

It has almost become an acceptable norm that hundreds of flights have been recalled to terminals after being air-born, numerous occasions of evacuation, passengers rechecked, or even asked to strip-off [1]. Airports and aircraft have significantly upgraded their security machinery and mechanisms, and where regional airports cannot afford these, they shutdown. Passengers frequently need to check relevant "travel warnings" and be prepared for any unexpected event to occur in the name of "terrorism" or "security".

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 terrorism threats [2]. 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 [2]. The

latest and fastest "InVision" technology can scan approximately 128-542 bags/hour - roughly two plane loads per hour [3].

In order to provide appropriate security, a much more sophisticated, reliable, and fast screening technique is needed for passenger identification and baggage examination. 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.

## 2. SECURITY SCREENING TECHNIQUES

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

Knowledge of simplified X-ray technology is necessary to understand the security detection problem. When an accelerated electron passes through a potential difference and is suddenly stopped by an object, the kinetic energy of those electrons is converted to heat and X-rays. The characteristic emission of electro-magnetic waves depends on a number of factors, including the property of the type of target (solid) material. Thus, the measured spectra of the radiated photons enable us to characterise the target material, such as atomic composition, density and thickness. There are many types of X-ray detectors available. All use some physical effect of X-ray on matter. 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 [4][5]. New X-ray imaging systems at airports use dual-energy analysis to estimate the atomic numbers of materials in the passenger baggage [6][7]. 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 [8]. Advanced X-ray luggage inspection systems are based on scattered X-ray energy imaging techniques, which gives better results, particularly in detecting plastic explosives [9].

Substantial improvements are required in existing techniques to meet the current security needs [2][8] – 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 [10][11]. Those techniques try to reconstruct a more precise 3D object using computed tomography (CT) 3D information [8][10]. 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. Some of these incorporate techniques developed and used for other applications.

## 2.1. Segmentation

Various forms of noise normally degrade X-ray images [12]. The raw image is, therefore, processed using a number of algorithms, which enhance the quality of the image, without removing any salient features such as edge information. The refined image pixels are then segmented to form regions that have some form of homogeneity in terms of grey levels or some other significance. The effective segmentation technique really depends on the type of application. Segmentation of images has been a very mature area and highly efficient techniques are available [13]. Much of these techniques are developed for handwriting recognition and face recognition problems.

## 2.2 Feature extraction

When the region of interest (ROI) is identified in the whole image, features need to be extracted from the segmented images. Such features may include average grey level values, rms values, standard deviation, entropy, area, edge information, colour, texture features, shapes etc. Feature extraction is more complicated when the image has overlapping objects. However, this problem is usually

addressed earlier in the detection process during segmentation. When 3D image analysis is used, additional information such as cues on depth can be extracted. Although feature extraction has been studied well for other applications, more significant features need to be identified for efficient detection of illicit materials [14][15][16].

## 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. However the classification rate in x-ray luggage scanning is well below satisfactory levels. The investigators' experience shows that ANNs can be very effectively used for feature extraction and classification in general [14][17].

### 2.3.1 Artificial Neural Networks

In the last two decades ANNs have emerged as powerful computational tools for analysing and learning complex, non-linear patterns for the purpose of pattern matching and classification. Due to their success in such areas as pattern recognition and prediction, ANNs have been applied to a large number of real world applications [18][19].

One methodology employed for teaching ANNs is that of supervised learning. Supervised learning is based on a direct comparison between the actual output of an ANN and the desired correct output, also known as the target output. One of the most successful supervised learning algorithms is the gradient descent-based optimization algorithm known as backpropagation (BP) [20], which is used to adjust connection weights in the ANN iteratively in order to minimise the error of the network.

Another popular ANN is the Hamming distance-based network[14]. The typical Hamming network used for classification has three layers. The network contains an input layer whereby the number of nodes is equal to the number of features. It has a category layer, with as many nodes as there are categories, or classes. And finally, there is an output layer, which matches the number of nodes in the category layer. The network is a simple feed-forward architecture with the input layer fully connected to the category layer. Each processing element in the category layer is connected back to every other element in the same layer, as well as to a direct connection to the output processing element. The output from the category layer to the output layer is done through competition. The connection weights are first set in the input to category layer such that the matching scores generated by the outputs of the category processing elements are equal to the

number of input nodes minus the Hamming distances to the example input vectors. These matching scores range from zero to the total number of input elements and are highest for those input vectors which best match the learned patterns.

## 2.4 Problems with Existing Techniques

Research into the development of accurate Computer Aided Screening (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 contribute to an increase in speed, a decrease of false alarms and increased assistance to human screening operators.

Our proposed techniques address the problems identified above through the adoption and extension of pattern recognition techniques in innovative ways.

## 3. PROPOSED TECHNIQUES

In this research we propose 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 is built mainly based on the following concepts:

- A novel object detection technique for locating illicit materials in cluttered x-ray imagery based on a classification-based algorithm using features extracted from the objects' boundary and additional texture information
- Integrating known intelligence data for enhancing the detection of illicit material

This proposed detection model incorporates the following novel techniques to enhance the accuracy and efficiency of the overall detection process. They identify the appropriate feature extraction technique, classification system, and a mechanism to provide a confidence rating. The confidence factor is derived by integrating the current security alert level with the extracted information from x-ray images. The three main components of the proposed models are:

1. The complimentary extraction of shape and texture information from grey-scale, x-ray images will provide an accurate description of objects based on local features. Both feature types will be investigated separately, compared and integrated using appropriate fusion techniques for the most effective object representation.
2. A novel, classification-based technique employing multiple neural networks trained on illicit object descriptions (features) shall be investigated for the detection of illicit objects in x-ray images. The automatic technique will provide the location of the illicit object along with a confidence rating to assist human operators at luggage screening stations.
3. To assist in providing a confidence rating, information obtained from an investigation of the x-ray image will be combined with known intelligence data from security alerts to provide a more effective convergence of evidence.

## 4. SYSTEM IMPLEMENTATION

### 4.1 System Overview and Feature Extraction

The main sub-tasks in this phase are to acquire the relevant data for experimentation, to perform image segmentation and subsequently feature extraction. A number of suitcases will be packed with illicit objects embedded in non-threatening materials to simulate real-world conditions. For the purpose of limiting the scope of the investigation and in part to address the urgent problem of detecting threat objects that have played a part in recent terrorist attacks [21], the illicit objects will be limited to knife-like and sharp objects (i.e. toe-nail clippers, box cutters etc). An initial database of twenty images of various suitcase configurations will be acquired using an x-ray machine. The x-rays will be scanned at high resolution and stored in a digital grey-level RAW file format, waiting further processing.

Once obtained, the digital images will require preprocessing to facilitate effective feature extraction. For this purpose, each image will need to be converted to a format that will facilitate image manipulation. We will convert each image to a Grey-scale, portable grey map (PGM) format. In the next step, images will all be segmented with an existing multi-threshold algorithm [22]. The segmentation stage will enhance the image so that objects therein appear clearer and more easily distinguishable for further processing. In further processing, each image will then be passed to an edge detection technique using the Matlab image processing toolkit in conjunction with supplementary software available to the investigators.

Once initial processing is complete, a novel approach for extracting features from the segmented images will be investigated for providing adequate inputs to the classification schemes. The first feature to be extracted will be a modified “direction feature” that will build on previous work conducted by one of the authors for character recognition [15]. This feature is based on the shape of an object and uses boundary information to calculate the directions of individual lines. It was highly successful when applied to the problem of character recognition, however it will be extended to extract critical points invariant to translation, rotation and scale as proposed by Freeman [23].

The second feature will be used in a complimentary fashion to the direction feature, and will describe the texture representation of objects in the image. The “texture feature” will build on previous work that the authors have undertaken for content-based image retrieval [14]. The basic premise of the technique is that images are transformed using a 2-Dimensional Fourier Transform (2D-DFT). Only the magnitude coefficient matrices are used for characterising the textures in the image. The matrices are normalised, and are reduced in size to provide an adequate input vector for neural network training. The main output of the phase will be a comprehensive database of preprocessed digital images, and subsequently appropriate features to be provided for training and subsequently testing in the next phase.

A high-level representation of the process from image processing through to feature extraction and object detection may be seen in Figure 1.

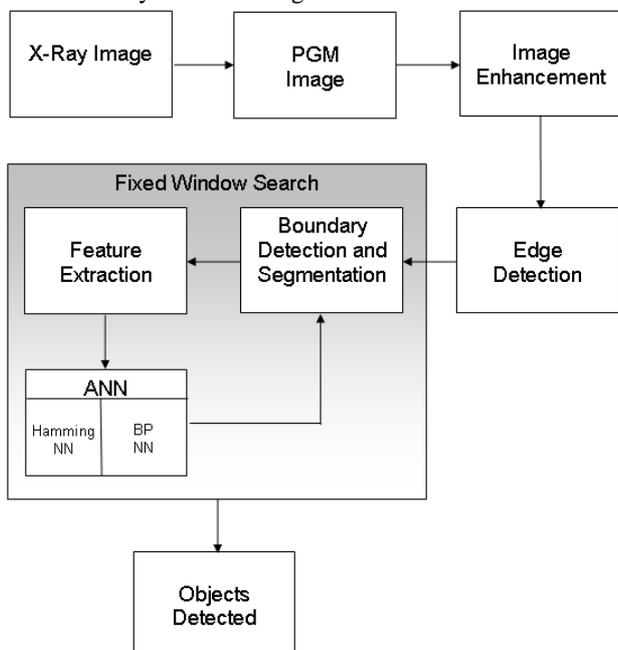


Figure 1: System Overview – Image Processing, Feature Extraction and Object Detection

## 4.2 Neural Network-based Classifier

The success in applying ANNs to many real world applications, including pattern matching and recognition, is the basis for their use in this project. ANN classifiers will be trained on representations of objects in x-ray images. The representations will be formed through various novel feature extraction techniques [14][15]. The classifiers will then be integrated into a classification-based system for determining the presence of illicit materials in luggage.

The main tasks in this module include the training of relevant classifiers and finally the development of a classification-based technique for detecting threat objects in x-ray images. The ANN that will be adopted for the process of classifying “direction features” will be a fully interconnected, feedforward ANN. The network will be trained using the backpropagation algorithm. For the process of categorising texture features, another type of feed-forward ANN will be used: The Hamming distance-based network.

Following the preparation of truthed data and subsequently training, the networks will be provided with the test data in the form of input vectors representing unknown categories of the illicit and non-threatening objects. The networks will then have the ability to classify the objects into “threatening” or “non threatening” categories generalizing upon its trained data and outputting a confidence for a given object. As more data becomes available, the neural network may be re-trained using further examples to strengthen its classification ability.

The classification-based procedure will employ a search strategy through the scene (x-ray image) using a fixed-size moving window (Figure 1). The original image (x-ray image) will be re-scaled to a number of different sizes whilst maintaining the size of the moving window. This will compensate for the variation in size of objects in the x-ray image. The image captured by the moving window at a particular instance will be preprocessed, features will be extracted and finally passed to the relevant classifier (depending on the type of feature extracted). A result of this processing, either “Threatening” or “Non-threatening” will be output based on the confidence of the particular classifier. At this stage the preliminary classification-based detection scheme will output confidences for two types of networks separately. In the next phase this raw information will be processed further. Figure 2 shows the concept of presenting feature data to a single ANN for confidence output.

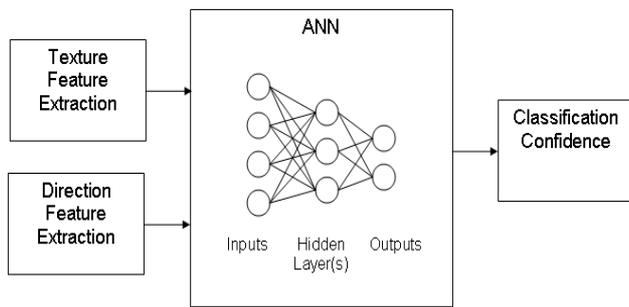


Figure 2: ANN training/testing with two types of features

### 4.3 Integration of Security Alerts

In the final module, further ANN experimentation will be required, along with fusion of classifier confidences and finally the integration of “intelligence information” into the decision process. From Section 4.2, a preliminary system will be completed for detecting objects in x-ray images and outputting classifier confidences. In order to obtain the highest accuracy in terms of the decision process, outputs from each classifier will be fused, based on an averaging and weighting system. Hence, to illustrate, if the classifier trained with the direction feature produced a high confidence value of a “threat object” and the texture feature classifier agrees with this assessment, the average would be a high value, and there would be a high probability that the object under examination is illicit. However, if the classifiers did not agree, the average confidence would provide a reasonable estimate which class an object belongs to. However, instead of outputting a raw confidence value, a system for delivering a qualitative alert is required to accompany the highlighted object based on appropriate thresholds to effectively represent the situation. The alert method chosen is based on fuzzy logic [24]. To represent measures such as the degree in which a classifier considers an object a “threat”, fuzzy logic introduces a set membership function that maps elements to real values between 0 and 1 inclusive. Fuzzy boundaries may be set so that if a classifier combination outputs a confidence of 0.8 (i.e. 80%), then the possibility of the object being illicit may be considered high or “high threat”. However, if the confidence obtained falls between the region of 0.5 and 0.79, then the object may be deemed a “medium threat”. This type of alert may require human intervention to ascertain whether the object in question is actually a threat object. Overall, this qualitative output provides a simple yet effective way for human operators to evaluate a potentially threatening situation. Figure 3 depicts this concept of fusion.

To further increase accuracy, a weight value will be assigned to individual confidences, whereby the most accurate classifiers (during training) could be given higher weighting (i.e. multiplied by 1.1) during testing. Finally, in addition to fusing classifiers, this research intends to make

use of qualitative/quantitative information available from defence intelligence - information from the appropriate authorities on such matters as threats made at particular airports, or the expectation of specific objects on a given day. These pieces of information could be used to enhance weighting of confidences during fusion, to initiate a more exhaustive search on x-ray images or to give priority to the detection of particular object types. Such information has not been considered in existing models of CAS systems but will be explored with specific cases during testing of the entire system.

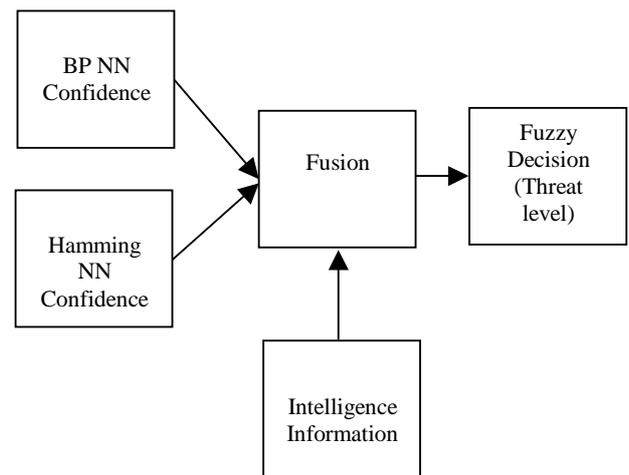


Figure 3: Fusion of Intelligence Information

## 5. CONCLUSIONS

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 proposed an intelligent illicit object detection model, which incorporates the fusion of novel shape and texture information for efficient representation of illicit materials. Then, an ANN-based classification system is proposed for the detection process. This system can also easily include any information from security alerts for efficient operation.

The most common method for screening luggage at airports is with the use of x-ray technology. There are a number of reasons why it is commonly adopted including safety factors and the fact that the technology is well

understood and relatively inexpensive. As digital x-ray technology becomes more prominent, and based on the current state-of-the-art in image processing, feature extraction and classification technology, the role of computers in screening luggage will increase in order to enhance manual screening procedures.

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