

# Weapon Detection and Classification Based on Time-Frequency Analysis of Electromagnetic Transient Images

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**Abstract**—Terrorist groups, hijackers, and people hiding guns and knives are a constant and increasing threat. Concealed weapon detection has become one of the greatest challenges facing the law enforcement community today. The fact that most weapons are made from metallic materials makes electromagnetic detection methods the most prominent and preferred approach for concealed weapon detection. Each weapon has a unique electromagnetic fingerprint, determined by its size, shape and physical composition. A new detection system developed at Newcastle University that uses a walk-through metal detector with a Giant Magneto-Resistive sensor array has been utilized in this study. The system enables a two-dimensional image to be constructed from measured signals and used in later image processing. This paper addresses weapon detection using time and frequency feature extraction techniques based on this new system. The study also employs and compares two classification techniques for potential automated classification. Experimental results using guns and non-gun objects in controlled and non-controlled environments have demonstrated the potential and efficiency of the new system. The classification capabilities of the system could be developed to the point that individuals could pass through the system without the need to take off other metallic objects. The proposed techniques have the potential to produce major improvements in automatic weapon detection and classification.

**Keywords**-sensor array; electromagnetic imaging; weapon detection; feature extraction; airport security.

## I. INTRODUCTION

This paper, based on previous work from Al-Qubaa et al. [1], presents new results for the proposed weapon detection and classification system. There is a growing need for effective, quick and reliable security methods and techniques using new screening devices to identify weapon threats. Electromagnetic (EM) weapon detection has been used for many years, but object identification and discrimination capabilities are limited [2]. Many approaches and systems/devices have been proposed and realised for security in airports, railway stations, courts, etc. The fact that most weapons are made of metallic materials makes EM detection methods the most prominent and systems/devices built on the principle of EM induction have been prevalent for many years for the detection of suspicious metallic items carried covertly [3]. Walk-through metal detectors (WTMDs) and hand-held metal detectors (HHMDs) are commonly used as devices for detecting metallic weapons and contraband items using an EM field. Most WTMD and HHMD units use active EM techniques to detect metal objects [4][5]. Active EM means that the detector sets up a field with a source coil and this field is used to probe the environment. The applied/primary field induces eddy currents in

the metal under inspection, which then generate a secondary magnetic field that can be sensed by a detector coil. The rate of decay and the spatial behaviour of the secondary field are determined by the conductivity, magnetic permeability, shape, and size of the target. Sets of measurements can then be taken and used to recover the position, the size and the shape of the objects.

Many other EM imaging techniques have been used in WTMDs. These methods include microwave [6], millimetre waves [7], terahertz waves [8], infrared imaging [9], and X-ray imaging which has been used for luggage inspections in airports [10]. All these approaches have advantages and disadvantages linked to operating range, material composition of the weapon, penetrability and attenuation factors.

Weapon detection systems currently available are primarily used to detect metal and have a high false alarm rate because they work by adjusting a threshold to discriminate between threat items and personal items, depending on the mass of the object. This leads to an increase in the false alarm level [11] [12]. Also, the human body can affect the sensitivity of the detector as when dealing with low conductivity or small materials, the human body can give a stronger signal than the material. This can cause the material to pass undetected, giving poor reliability [13]. Advanced signal processing algorithms have been used to analyse the magnetic field change generated when a person passes through a portal. Then pattern recognition and classification techniques can be used to calculate the probability that the acquired magnetic signature correlates to a weapon, or whether it is a non-weapon response [14].

Extracting distinct features from the EM signal is imperative for the proper classification of these signals. Feature extraction techniques are transforming the input image into a set of features. In other words, feature extraction is the use of a reduced representation, not a full representation, of an image to solve pattern recognition problems with sufficient accuracy. Extract or generate features from the EM signal is common method for metal detection and classification to represent the possible targets of interest. Feature extraction using Time-Frequency analysis has been used for stationary targets of backscattered signal [15]. Features are extracted from scattered field of a given candidate target from the joint time-frequency plane to obtain a single characteristic feature vector that can effectively represent the target of concern. Joint time frequency analysis was used to overcome the limitation of using the Fourier transform (FT) series to represent the EM signals which is require an infinite number of sinusoid functions [16]. The sinusoid function

provides a feasible way of computing the power spectrum for EM signal, which is serves as unique fingerprint of the weapon detection response to various targets, i.e., weapons, cell phones, etc. [17].

The literature review revealed that wavelet transform (WT) are a successful method for the signal representation of time series data such as EM signals [14][18]. WT has been used to represent time series data such as ECG waveforms and mine signal detection [19]. The WT can be thought of as an extension of the classic FT except operating on a multi-resolution basis. The results obtained from [20] verify that the WT based technique produces features that are suitable for detect and identify metallic targets signal data.

After Feature extraction step, the images can be displayed for operator-assisted weapon detection or fed into a weapon detection module for automated weapon detection and classification. In [21], authors present an artificial neural network (ANN)-based scheme for metal target detection and classification. The proposed strategy involved the use of various neural networks schemes for performing feature extraction and classification tasks. It was shown that the use of an ANN in multispectral wavelengths provided a useful tool for target detection and classification. In [14], a case study on classifying metal detector signal for automated target discrimination is conducted. In this research an adaptive resonance theory networks was used and the results indicate that ANN has a vital role to improve the performance of classification. In [10], probabilistic ANN classifier used to classifies the extracted weapon candidate regions into threat and non-threat objects. The proposed framework is evaluated on a perfect database consisting of various weapons in different size, type of gun and real images and 96.48% accuracy rate has been obtained. In [22], the ANN used to differentiate between different target types such as a Glock or a starter pistol. A combination of techniques is presented that enables handguns to be effectively detected at standoff distances. Late time responses that allow threat from innocent objects (e.g., mobile phones, keys, etc.) to be distinguished from handguns. Information about the optical depth separation of the scattering corners, and the degree and shape of cross polarization allows ANN to successfully detect handguns in that research.

Support Vector Machine (SVM) has been used recently as a new machine learning methods. SVM is a concept in statistics and computer science for a set of related supervised learning methods that analyse data and recognize patterns, used for classification and regression analysis [23]. In [24], the authors revisit an attractively simple model for EM induction response of a metallic object using SVM to train and produce reliable gross characterization of objects based on the inferred tensor elements as discriminators. They focusing on gross shape and especially size to evaluate the classification success of different SVM formulations for different kinds of objects, and noticed that SVM has an inherent limitation that it takes a very long time to yield an answer in some instances. In [25], the problem of classification metallic objects using their EM induction response is solved by decomposing that response into coefficients and then using SVM and ANN to process those coefficients. The performance of each

method is compared. Since it demonstrate that there is no simple relationship between sizes of objects and the overall magnitude of their coefficients, learning algorithms are necessary and useful in classifying these objects. When trained on all types of objects, both the ANN and the SVM are able to classify all objects with a good degree of accuracy. In addition, both methods show an ability to generalize for noisy test data when trained with noisy data.

A new detection system developed at Newcastle University [26] and built in a lab using an ex-service CEIA WTMD, with the addition of a Giant Magneto-Resistive (GMR) sensor array to capture the EM scattered data from any metallic objects, is used in this study.

The contributions of this paper are: firstly, improve the characterization capabilities of the new detection system through investigation of the effect of different orientations as well as the effect of concealed weapons. Secondly, investigate the feasibility of extraction features from WT and FT for weapon detection. Thirdly, automatically recognize and classify metallic threat objects by using of Support Vector Machine (SVM) and Artificial Neural Network (ANN) as classifiers.

The rest of this paper is organized as follows. Firstly, the system design and principles of operation are introduced in Section II. Next, system efficiency and test validity are reported in Section III, which is followed by details of the feature extraction methods used in Section IV. Section V explains the classification techniques used. Section VI demonstrates the classification test bed setup. Classification results are discussed in Sections VII. Finally, the conclusion is outlined in VIII.

## II. SYSTEM DESIGN AND PRINCIPLES OF OPERATION

In this section, a brief description of the detection system will be given with the EM images capturing condition.

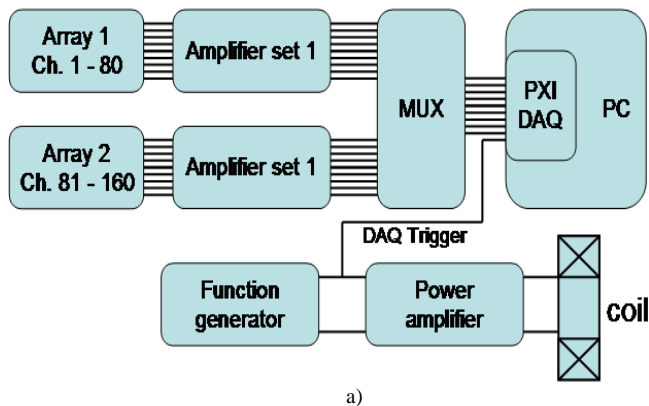
### A. System design

The system used for the experimental tests is based around an array of NVE GMR sensors used in conjunction with the excitation coil in an ex-service CEIA (*Construction Electronics Industrial Automation*) WTMD. Figure 1 shows a block diagram of the system, the new system being converted from a typical walk through metal detector system. The signals from the sensor array are amplified using an array of signal amplifiers based on an INA111 instrumentation amplifier. Data acquisition is performed using an 80 channel PXI based National Instruments data acquisition system. The use of the PXI based system allows data to be acquired on 40 channels at a rate of 125kS/s, or 80 channels at a rate of 62.5kS/s. The channel count is further increased to a maximum of 160 by the use of multiplexer circuits. A variable excitation waveform is provided by a function generator, the signal from which is also used for data acquisition synchronisation.

The AAL002-02 GMR sensors were chosen because of their sensitivity and noise suppression compared with other common sensors such as Hall Effect models. The L in the sensor model name indicates that low hysteresis (maximum 2%) GMR material has been used to fabricate the sensor. This was chosen because it was initially intended to utilise an applied magnetic field varying

from 0 to a maximum value and the lower hysteresis would minimise errors at low fields. However, after initial tests it was found that a more stable signal could be achieved by biasing the sensor response into its linear region using a DC offset superimposed on the excitation signal.

After several experimental studies the GMR sensor array was superimposed on the coil found inside the arch coil panel. The coil was positioned after taking an x-ray of the WTMD panel, and making investigation for signal measurements as shown in Figure 2.



a)



b)

Figure 1. Proposed EM system (a) Block diagram, (b) System setup in the laboratory [34].

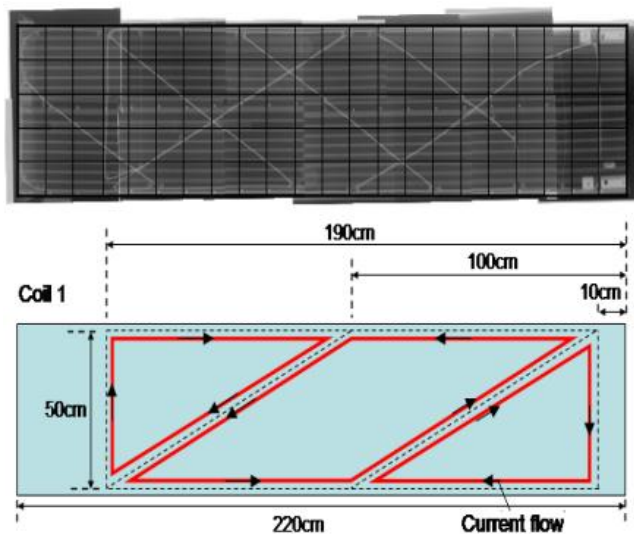


Figure 2. Coil position inside the WTMD panel.

*B. Electromagnetic field imaging*

Figure 3 illustrates the different metallic objects and their equivalent EM field images. The samples represent common threats and personal objects carried by people.

The tests were carried out using a 40 sensor array and a sample rate of 125 kHz. Thus, the temporal EM field distribution as the object moves past the array can be determined. The sensors array is aligned with the coil to pick up any distortions in the applied field due to the presence of metallic materials. Five experiments were carried out with each item and their capturing condition being summarized also in [26].

The interaction between the applied field and any sensor in the array can be captured and the pulse response from a group of sensors can be stored by moving the objects, as shown in Figure 4. If no object is present in the WTMD, the field measured by the sensor is unchanged; the presence of a metallic object causes distortion of the field, which can then be measured by the sensor.

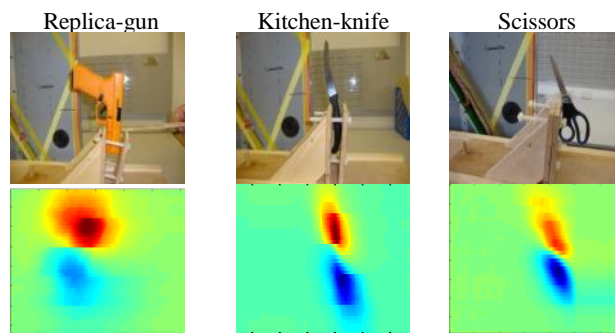


Figure 3. Samples with the equivalent EM images.

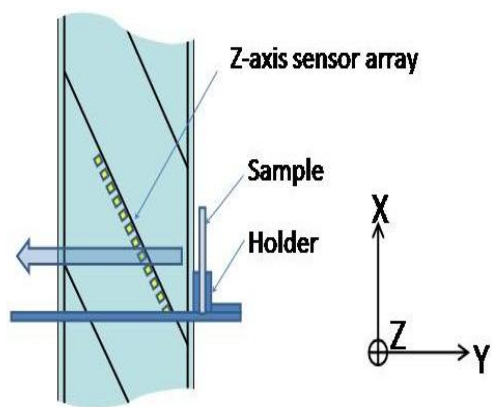


Figure 4. Object test set-up.

In the proposed system, pulsed excitation is applied to the coil. Pulsed excitation provides the opportunity to apply an interrogating field with rich frequency components in a single waveform. In the tests detailed in this paper, a pulse repetition frequency of 500Hz was used with a pulse width of 1ms and an applied current of 0.5A – 1.5A.

### III. SYSTEM EFFICIENCY AND TEST VALIDITY

This section explains different experimental setups used during tests to improve the ability and efficiency of the detection system. Also, repeatability is examined to check the validity and to confirm the measurements.

#### A. Different orientation experimental setups

To check validity of the proposed system, experiments were carried out to study the reflected signals from objects under different orientations.

Figure 6 shows the test set-up for different orientations. The objects were moved past the array dynamically and data were taken while the object was moving. Data were taken with the samples orientated in three directions.

The results of the orientation test for the kitchen knife sample are shown in Figure 6. It can be seen from the images that the feature map follows a fairly predictable evolution with the rotation of the object; in the x-direction and y-direction the object appears as a dipole distribution, with the rotation of the distribution correlating to the rotation of the object. In the z-direction, only one end of the “dipole” is presented to the array, so a uni-polar distribution is observed.

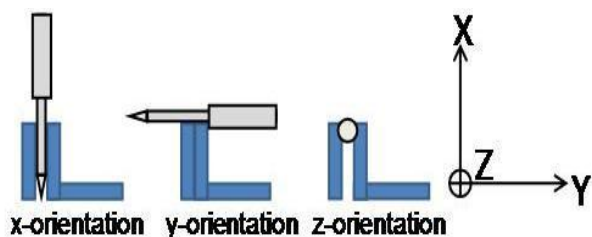


Figure 5. Orientation Test set-up

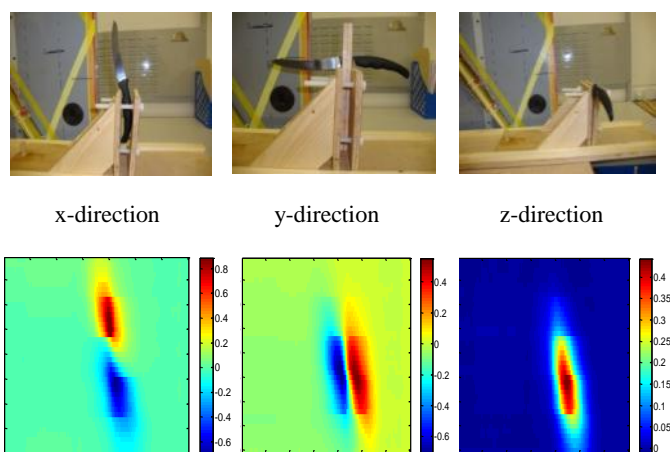


Figure 6. Different orientation results from kitchen knife sample test.

A similar trend follows for all objects; the object appears as two peaks in the feature map and as the object is rotated, this distribution is rotated from the x-direction image to the y-direction image. The z-direction, though, exhibits a clear uni-polar distribution; this is mainly due to the dimensional configuration of the sensor array.

#### B. Real weapon experimental setup

In order to verify the new system effectiveness using real threatening items, a series of tests using real handguns was carried out. This section reports some of the results from these tests.

Six real handguns are used (borrowed from a police station) and the specifications of these handguns are listed in Table 1. Figure 7a shows the handguns in the sample holder constructed for the tests and their reflected EM images are shown in Figure 7b. The holder was configured to ensure that the samples retained a constant and comparable distance and orientation with respect to the array during each pass through the system.

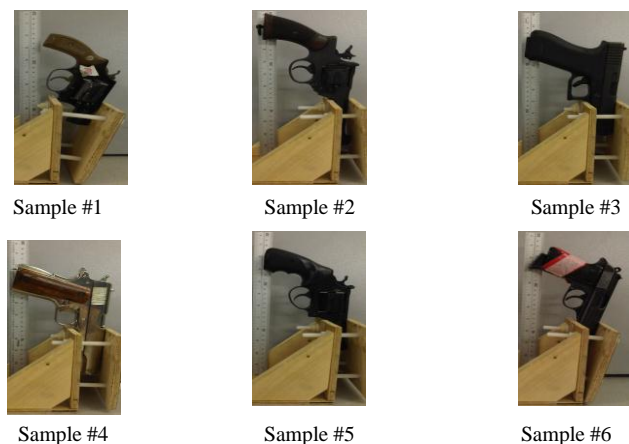
Table 1. SPECIFICATION FOR THE ALL HANDGUNS.

Sample	Description
1	Small revolver – 0.38” Smith & Wesson – Deactivated.
2	Revolver – 0.38” Enfield service revolver – Deactivated.
3	Large automatic – 9mm Glock G17 – Live.
4	Large automatic – 0.45 Colt M1911 – Replica.
5	Small revolver – Brocock Puma air pistol – Live.
6	Small automatic – 7.65mm Walther – Deactivated.

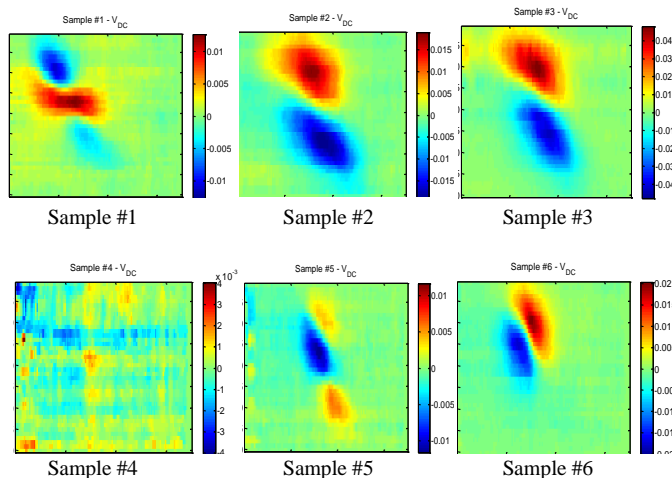
The test samples were representative of a range of handguns which would be of interest for detection. In general, it is unlikely that the deactivated weapons would give a drastically different response to the same live weapon. Although the presence of

ammunition clearly increases the volume of material within the arch, it would not affect results significantly.

through the arch. Test results are shown in Figure 8b. The EM images for the objects are clearly compressed along the x-axis compared to the controlled tests, due to the object moving through the arch at a greater speed; however, the actual distributions remain very similar.



a)



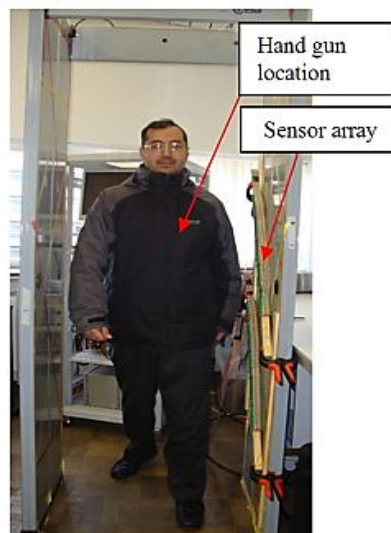
b)

Figure 7. Handgun samples (a) In sample holder, and (b) Reflected EM image results.

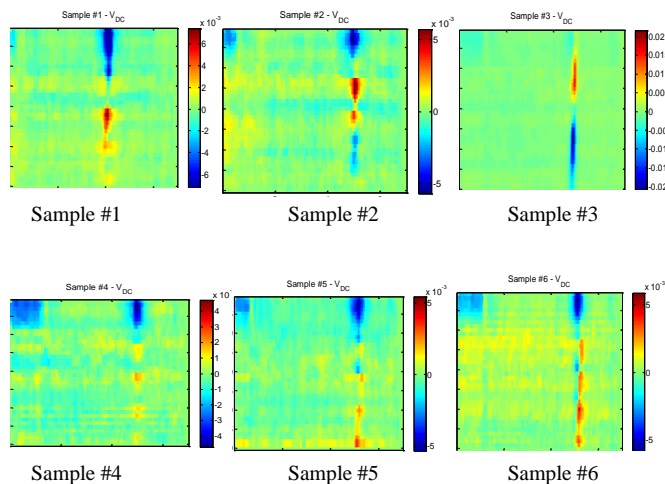
The first set of tests was carried out in the same way as the previous detection tests (explained in Section II above). Results are shown in Figure 7b and are generally good, as would be expected for the controlled test setup. The one exception is sample 4, the replica gun, which is very difficult to locate in the test results. It had the lowest amplitude response and therefore the poorest signal to noise ratio.

It is notable that samples 2 and 3 gave similar results, responding to a type of dipole distribution, indicative of a ferromagnetic object made predominantly from a single type of metal. The simple form of distribution also indicates that there is very little metal in the handle of these objects, and the array saw them as a simple tube/block of metal.

Another test setup for the uncontrolled walk-through tests using real handguns is shown in Figure 8a. The handguns were carried in the inside jacket pocket of an individual walking

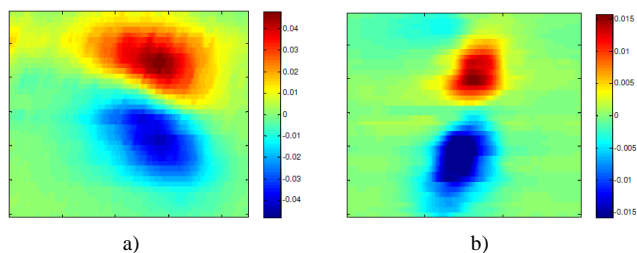


a)



b)

Figure 8. Walk-through test (a) Test set-up, (b) Results for all hand guns from the walk-through test.



a)

b)

Figure 9. EM images for the sample #3 - a) Controlled, b) Uncontrolled tests.

Figure 9 shows the EM images for the controlled and walk-through tests using the handgun sample #3. The results from the walk-through test have been expanded along the horizontal axis compared to Figure 8b to aid comparison. Comparison of the plots shows that although the controlled and walk-through tests did not give identical results, the general form of the EM signatures was roughly similar. Thus, using appropriate analysis techniques it can be ascertained that the signatures are from similar, if not the same object.

### C. Measurement Stability

In this subsection, system stability is checked by examining the repeatability of the experimental tests using a simple amplitude calculation. The overall amplitude change for each EM signal is plotted for five repetitions of the test for all handgun samples. The overall amplitude change is computed by subtracting the maximum from the minimum value of each EM signal received. The results are plotted in Figure 10 for both the controlled and walk-through test. It can be seen from Figure 10a that, the controlled test has the greatest repeatability. As well as the data trend is similar for the walk-through test as showed in Figure 10b.

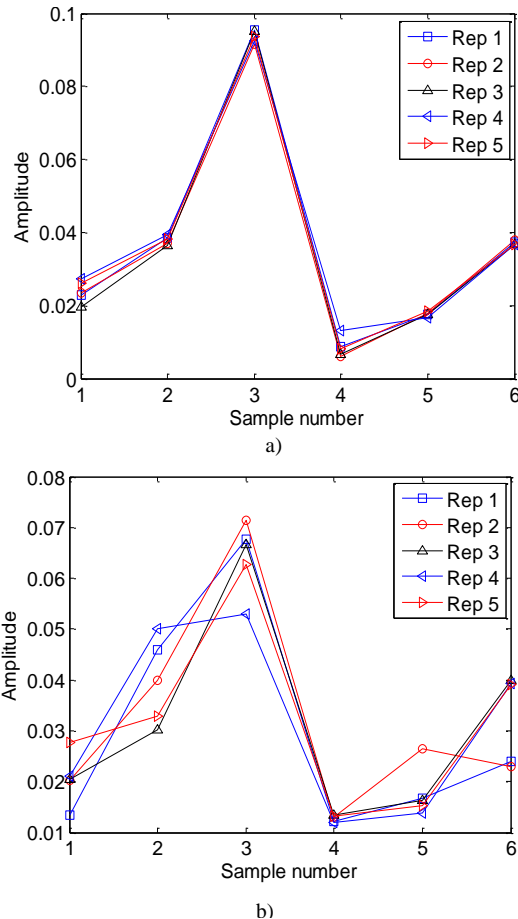


Figure 10. Overall amplitude change for (a) Controlled test, (b) Walk-through test.

## IV. FEATURE EXTRACTION TECHNIQUES

Features were extracted from two different techniques (FT and WT). A brief background of FT and WT will be provided, with the motivation behind their use. In addition to detailed the feature extractions algorithm.

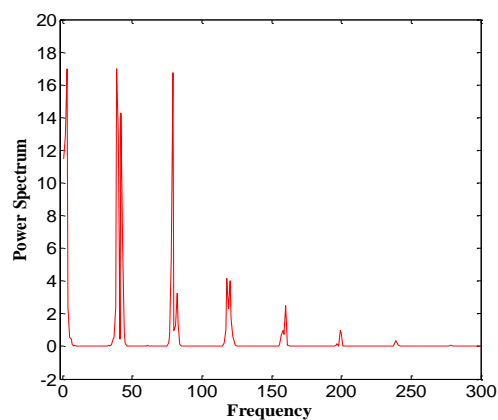
### A. Fourier Transform (FT)

The Fourier series provides an alternative way to represent data; instead of representing the signal amplitude as a function of time, we represent the signal by how much information is contained at different frequencies. Fourier analysis is important in data acquisition as it allows one to isolate certain frequency ranges. The bridge between time and frequency representation is the FT. The signal can be decomposed as a weighted sum of sinusoid functions. This provides a feasible way of computing the power spectrum for a signal. Fast FT (FFT) is a fast algorithm of the discrete FT that represents the signals in the frequency domain. The power spectrum serves as the fingerprint of the analysed signal [16]. The absolute value will provide the total amount of information contained at a given frequency [27], and the square of the absolute value is considered the power of the signal. In this work the power spectrum (PS) of FFT for each EM image using the outcomes from the control test were utilised as a feature; each sample gave different PS, as shown in Figure 11.

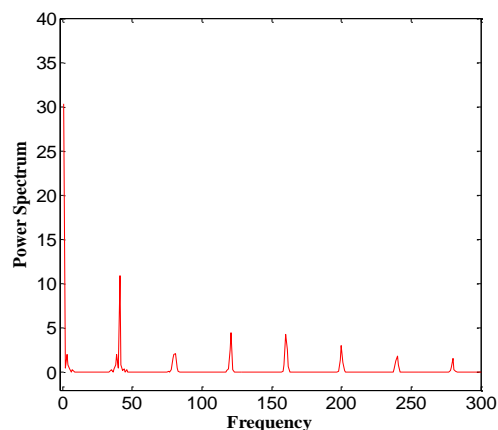
The PS results will be  $(n*m)$ , so to reduce the data size before applied to the classifier, Principle component analysis (PCA) techniques [28] was applied and first three PCA components were selected as it represent a 99.6% of the data variance. Figure 12 shows the behaviour of the PCA feature vectors extracted from the FFT process. The test was done using the six handguns with the different other not-threat objects. It is clear from the figure that the handgun #4 gives very low response because it consists of plastic material as well as the mobile phone object gives high response because it is full charged. Figure 13 shows the flowchart of the gun classification procedure using FFT features.

### B. Wavelet Transform (WT)

In contrast to FFT, Wavelet analysis is useful in decomposing a time series into time-frequency space simultaneously. The analysis provides information about both the amplitude of any "periodic" signals within the series, and how this amplitude varies with time. WT can be considered as an extension of the classic FFT except that it operates on a multi-resolution basis. This multi-resolution property enables a signal to be decomposed into a number of different resolutions. Each resolution represents a particular coarseness of the signal. Preservation of spatial information is another property of WT after transformation. This enables the identification of areas in the original signal that correspond to particular characteristics present in the WT data [29].



a)



b)

Figure 11. Part of the power spectrum of (a) Handgun, (b) Mobile Phone.

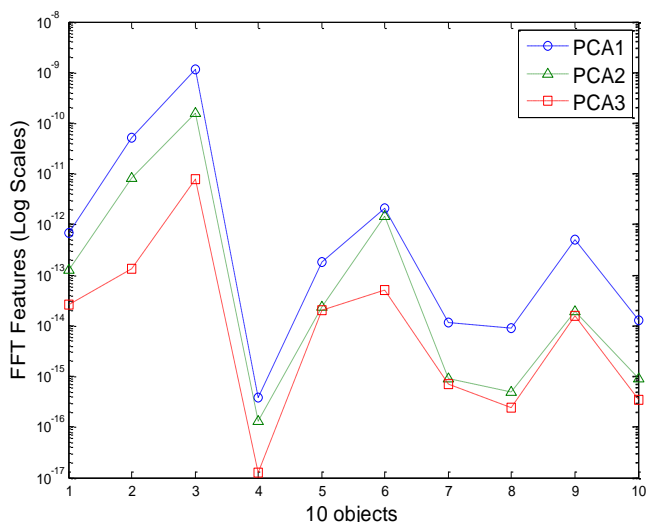


Figure 12. Feature vector extracted from the FFT process for 10 objects, #1-#6 are threat items (handgun samples) and the others (#7-#10) are not-threat items (Camera, House Key, Phone and Pen) as sorted number in the figure respectively.

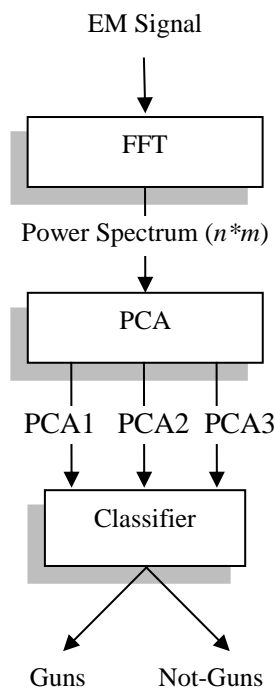


Figure 13. Flowcharts of the detailed gun classification procedure using FFT features.

The motivation behind using WT came from a preliminary analysis of the raw metal detector signal data. Literature proves that WT can be applied successfully as a method of signal representation of time series data. An example of this, is its application to electrocardiogram signals, which share a similar resemblance to metal detector signals [30][31]. Previous research also verifies that WT can be used to produce suitable features from metal detector data for target classification [14][32].

In this study, a discrete WT has been used. ‘Discrete’ refers to its discrete sets of dilation and translation factors, and discrete sampling of the signal. At a given scale,  $J$ , a finite number of translations were used in applying multi resolution analysis to obtain a finite number of scaling and wavelet coefficients. The signal can be represented in terms of the following coefficients (Eq. 1) [33]:

$$f(x, y) = \sum_k C_{JK} \varphi_{JK}(x) + \sum_{j=1}^J \sum_k d_{jk} \psi_{jk}(x) \quad (1)$$

where  $\varphi_{JK}$  are the scaling functions,  $C_{JK}$  are the scaling coefficients,  $\psi_{jk}$  are the mother wavelets and  $d_{jk}$  are the wavelet coefficients. The first term in Eq. (1) gives the low resolution approximation of the signal, while the second term gives the detailed information at resolutions from the original down to the current resolution  $J$ . Daubechies order 4 has been selected from the wavelet family and three levels of wavelet decomposition have been computed [32].

Three types of statistical operation were selected from the wavelet approximation coefficients (LL) domain to be considering as a unique feature for each object, namely Entropy, standard deviation (STD) and root mean square error (RMSE). Figure 14 shows the ENT, STD and RMSE features for the three WT levels using same 10 objects in the previous test, the six handguns and the others are the not-threat objects. It can be seen from the figure that these feature give good indication to identify between handguns and the other objects. However, some of the not-threat objects are close to the handguns features, such that the entropy of the house key for instance. This leads to combine wavelet features with the FFT features to give a good classification result.

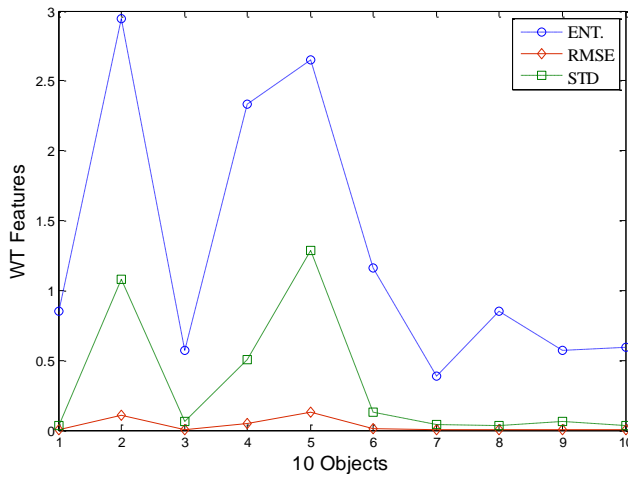


Figure 14. Wavelet features for 10 objects, #1-#6 are threat items (handgun samples) and the others (#7-#10) are not-threat items (Camera, House Key, Phone and Pen) as sorted number in the figure respectively, for one level WT analysis.

As a result, each EM image had three types of features with three levels of decompositions. Thus, a feature vector was generated consisting of nine values to be fed to the classifiers. A flowchart of the gun classification procedure using the control test and features obtained from the WT coefficient is shown in Figure 15.

## V. CLASSIFICATION TECHNIQUES

In this work, two different types of classification techniques have been applied and compared to evaluate the features which extracted from the new system and to adopt the efficient classification technique for an automated process. In previous work [1], the classification of different objects was performed using cross correlation technique. In this work, the classification has been performed using ANN and SVM techniques.

### A. Classification using Artificial Neural Network (ANN)

Neural networks are widely used in pattern recognition and classification since they do not need any information about the probability distribution and the priori probabilities of different classes. In this study, two feature vectors (WT and FFT) were

used as an input to an ANN classifier alone and in combination with each other to find out the most suitable features for classification.

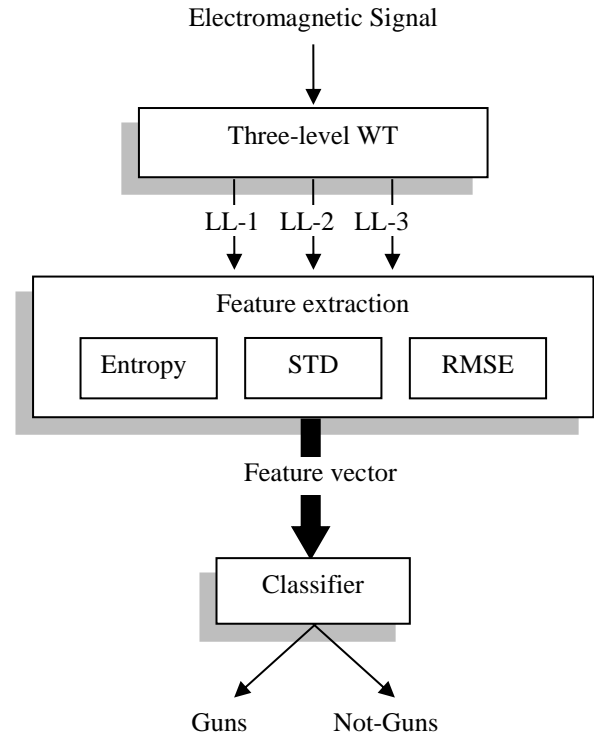


Figure 15. Flowchart of the gun classification procedure using discrete WT features.

A three layered ANN classifier was used: input, hidden and output layer. The input layer use the input feature vector element  $N$ , the hidden layer consisted of  $2N$  nodes with the sigmoid activation function. The output layer consisted of one node (for our study, symbolizing whether it is a gun or not) with a linear activation function. The ANN classifier utilized a training function based on Levenberg-Marquardt optimization [34]. All ANN parameters are summarized in Table 2.

Table 2. ARTIFICIAL NEURAL NETWORK PARAMETERS.

<b>No. of nodes in Input layer</b>	: Same no. of used feature vector elements ( $N$ ).
<b>No of nodes in Hidden layer</b>	: Double no. of used feature ( $2N$ ).
<b>No of nodes in Output layer</b>	: One node (Gun or not).
<b>Transfer function</b>	: 'logsig' for hidden layer, 'purelin' for output layer
<b>Training function</b>	: 'trainlm'
<b>Max number of Epochs</b>	: 10000
<b>Min performance gradient</b>	: 1e-10



### B. Classification using Support Vector Machine (SVM)

SVM is a concept in statistics and computer science for a set of related supervised learning methods that analyse data and recognize patterns. It is used for classification and regression analysis. SVM tackle classification problems by nonlinearly mapping input data into high-dimensional feature spaces, wherein a linear decision hyper plane separates the two considered classes. Different kernel functions nonlinearly maps samples into the higher dimensional space. Among them, the RBF Kernel is the most generally used. In many pattern recognition applications, SVM generalization performance is either similar or significantly better than other competing methods. In opposition to ANN, SVM have few hyper parameters to be adjusted [35].

In this work, a SVM based method was used as a second classification method to make a comparison with the results of ANN. The four feature vectors were normalised to the range [-1, +1] in each column first. The advantages of scaling are that it avoids attributes in greater numeric ranges dominating those in small numeric ranges, and it avoids numerical difficulties during calculation. In this work, the Radial Basis Function (RBF) was used as a kernel (K), as in Eq. 2 [23]:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \quad \gamma > 0 \quad (2)$$

The RBF kernel nonlinearly maps samples into a higher dimensional space. Thus, it can handle the case when the relation between class labels and attributes is nonlinear. Furthermore, the linear kernel is a special case of RBF. Finally, the RBF kernel has fewer numerical difficulties. The LIBSVM, a library for SVM developed by Chang and Lin [23], was used in this work. After training data using SVM, the model was obtained for prediction of known objects. The model was tested using the training data to identify the classification rate.

## VI. CLASSIFICATION TESTBED SETUP

Experiments were conducted with the new EM system to classify between guns and non-gun objects. The sample group consisted of twelve different objects. Six of the objects were handguns, while the others were commonly used objects that contain metallic parts. The specifications of all objects used are given in Table 3.

The handgun samples represent the most common weapons seized by the police; of particular interest is sample #5, the blank firer, which had been converted to fire live ammunition by the welding of another barrel to the existing mechanism, and the replica hand gun, sample #6, commonly used by armed robbers as a threat.

All samples constructed for the tests were controlled by a sample holder. The holder was configured to ensure that the samples retained a constant and comparable distance and orientation with respect to the array during each pass through the system. All weapon sample compositions included steel, with

several incorporating other materials such as zinc alloy, aluminium, and polymers.

Table 3. OBJECTS USED IN EXPERIMENTAL TEST: (A) REAL GUNS AND (B) COMMONLY USED OBJECTS.

(a) Real Guns		(b) Other Objects	
#1	Small revolver 0.516g	#7	Mobile phone
#2	Small semi-automatic 0.637g	#8	wristwatch
#3	Medium revolver 0.937g	#9	House Key
#4	Medium semi-automatic 0.689g	#10	Screwdriver
#5	Converted blank firer 0.800g	#11	Scissors
#6	Replica 1.140g	#12	Kitchen knife

Differences between two EM signals for two different objects were found to be close to the differences between two EM signals for the same object in two tests [26]. This conclusion was used to increase the number of samples; each object was tested five times using the new system to generate five EM samples for the same object. Hence, for the twelve objects under test, six were guns and six were non-gun objects, 60 EM samples were generated. Based on this, the classifier was trained using 48 samples for all objects (four for each object) while the remaining 12 samples were used as test samples as explained in Table 4.

Table 4. DATA SET OF THE WORK

Total No. of Images used= 60			
No. of training images = 48		No. of testing images = 12	
Guns	Non-Guns	Guns	Non-Guns
24	24	6	6

## VII. CLASSIFICATION RESULTS AND DISCUSSION

In this section, an assessment of the proposed features for object classification is carried out using the two classification methods.

Firstly, each type of feature vector individually provides for the ANN and SVM as inputs. The results are shown in Table 5 and 6 respectively. It can be seen from the tables that there is a major difference between ANN and SVM, that while the overall classification rates are largest when using the ANN classifier, the SVM classifier is more sensitive and shows 0% misdetection of the guns group. Although both classification methods give a high detection rate in terms of handgun objects, both methods give a high misdetection rate for non-gun objects. This is because training on these objects is not efficient due to the

diversity in their sizes, shapes and materials. The classification results could be improved using a larger database size [35].

Table 5. RESULTS OF ANN FOR EACH FEATURE VECTOR.

Feature vector	Hidden layer neurons	Objects	Correctly classified	Incorrectly classified	Classification rate
<i>WT</i>	18	Gun	5	1	83%
		Non-Gun	5	1	83%
			10	2	<b>83%</b>
<i>FFT</i>	6	Gun	5	1	83%
		Non-Gun	3	3	50%
			8	4	<b>67%</b>

Table 6. RESULTS OF SVM FOR EACH FEATURE VECTOR.

Feature vector	Objects	Correctly classified	Incorrectly classified	Classification rate
<i>WT</i>	Gun	6	0	100%
	Non-Gun	2	4	33%
		8	4	<b>67%</b>
<i>FFT</i>	Gun	6	0	100%
	Non-Gun	1	5	16%
		7	5	<b>58%</b>

Figure 16 shows the classification results with the average error from the ANN and SVM techniques.

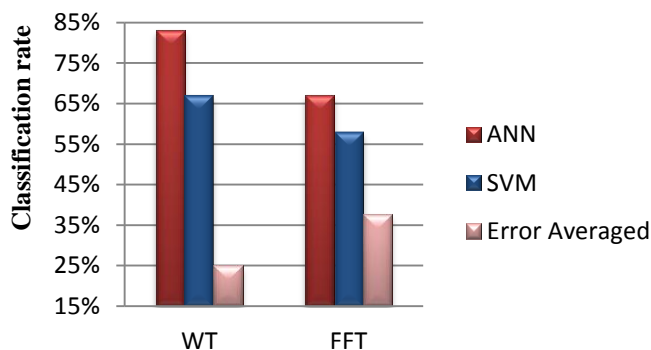


Figure 16. Classification rate results of ANN and SVM using WT and FFT features.

### VIII. CONCLUSION AND FUTURE WORK

This paper has demonstrated an EM metal detector system and investigated the feasibility of object identification and classification. In comparison with conventional induction based WTMDs, the new GMR array based system has shown great potential in objects classification as the samples are made from mixed material is identified. Whereas the induction based WTMD can only discriminate between metal and non-metal

object, this system has taken it a step further. Results obtained using the WT and FFT-based features have been given in detail to show the validity of the new system. The proposed features is more advanced in object characterisation as it depends on the amplitude distribution of the EM field making training possible using a database of objects; unlike traditional thresholding adopted in the induction based system, which largely depends on material volume. These features were utilized to classify 12 objects. Six were real handguns and six were different commonly used metallic items. The real handguns were examined in a controlled and uncontrolled environment such that the handguns were either controlled by a holder or carried on the inside of a jacket pocket of an individual walking through an arch. A comparison between two classification methods, ANN and SVM, showed promising results for detecting and classifying objects in security applications of EM signal. To conclude, WT features, due to their spatial frequency properties, showed almost better classification rates than FFT features, which have frequency properties. In terms of classifiers, ANN classification techniques have a better classification rate in general. However, SVM had very high sensitivity and showed very low false negative alarm (100% classification rate) in terms of handgun samples. These initial results aimed to identify possible methodologies for analysis and classify of EM signals.

For future work, the classification capabilities of the system could be developed to the point that individuals pass through the system without removing metallic objects from their person. This would be realised through "training" the system to identify threat objects by presenting the system with a wide variety of threat and non-threat objects. Further work can also utilize more EM features for accurate detection and classification of threat objects.

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