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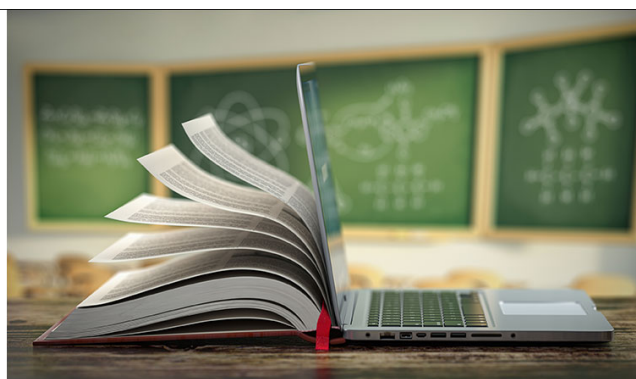
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Classification of metallic targets using a single frequency component of the magnetic polarisability tensor

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Abstract. A k-nearest neighbour (KNN) classification algorithm has been added to a walk-through metal detection system which is capable of inverting the magnetic polarisability tensor of metallic targets at a frequency of 10 kHz. Pre-computed library data is used to determine the class of the object, e.g. 'knife' or 'mobile phone', and is consequently capable of determining if an object is considered a threat. The results presented show a typical success rate of 95%. An investigation into classification accuracy between different candidates is also presented to determine the significance of the *body effect* on the success of the classification.

1. Introduction

Modern walk-through metal detectors are incredibly sensitive, precision measurement systems. Their widespread use for detection of threats in environments such as airports, prisons and public buildings, combined with the competition between several leading manufacturers has ensured that the current generation of technology is capable of detecting very small items such as handcuff keys and integrated circuits [1]. In the aviation industry metallic threats are principally considered to be knives and guns and are thus considerably larger than the smallest detectable objects. Improved signal-to-noise ratios may continue to be sought by manufacturers in an attempt to increase the detectability of non-magnetic, low conductivity materials such as some stainless steels, however the most significant challenge is no longer to detect the objects, but to determine whether they present a threat or not.

It is reported that between 2000 and 2010 a total of 17 out of an estimated 310 million commercial flights were hijacked worldwide [2]. Using these numbers it is estimated that in this ten year period the chances of a plane being hijacked was in the region of 1 in 18.2 million. This statistically rare threat can be contrasted with the fact that in environments such as airports it is common for people to carry several innocuous items such as mobile phones, jewellery, or keys, and current regulations require that travellers must remove these items prior to screening. This causes a great deal of disruption and inconvenience, and requires a large number of staff to administer. These facts demonstrate that any method capable of determining which items located on a person are threatening, and which are innocuous has the potential to greatly improve the aviation industry.

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In this study, a tomographic metal detection system [3] which is capable of inverting the magnetic polarisability tensor, $\bar{\mathbf{M}}$, from a single walk-through scan has been used as the measurement system. A library of tensors produced by this system has been recorded for a variety of different objects. To examine the capacitive and inductive effect of the human body on the measurements, known as the *body effect*, a separate library using two candidates has been collected. A classification algorithm based on the k-nearest neighbour (KNN) approach has been implemented, and the performance of the algorithm is tested for both the general library case, and the body effect case.

Although the method which is reported here is done so with focus on the aviation industry, the methods documented in this paper may be applied to any system which is capable of yielding the magnetic polarisability tensor; including detection systems for UXO/landmines.

2. Method

2.1. Producing the library

The library was constructed by simple walkthroughs using the WTMD described in [3]. This system uses eight pairs of transmit-receive coils, each of which operate at a different frequency. These frequencies range from 8 kHz to 13.8 kHz and are arranged lowest to highest from floor level upwards, with a separation of approximately 700 Hz between neighbouring channels. The system inverts a single tensor, and consequently offers only a single point on the tensor's continuously varying frequency spectrum [5]. Theoretically the inverted tensor is valid at the frequency corresponding to the parallel channel which is level with the object, however to for simplification and as the range of operating frequencies is relatively small the tensors are assumed to correspond to a frequency of 10 kHz – the median frequency value centred about the average height of candidates.

The library was constructed by repeatedly conducting walkthrough measurements. One object was carried through the detector at a time per scan, and its orientation and position on the candidate was varied between scans. The library contains a total of 33 different objects, and was built using data from 1316 walk-through scans. These scans were conducted using three different candidates. The objects belong to 10 different classes which are shown below. Numbers in brackets represent the total number of measurements per class.

- | | | | |
|---------------------|---------------------------|------------------------------|-----------------------------------|
| • Belts (40) | • Knives (424) | • Pocket Mirrors (50) | • Guns and gun parts (352) |
| ○ 1 belt | ○ 11 knives | ○ 1 pocket mirror | ○ 2 guns |
| • Coins (80) | • MP3 Players (80) | • Mobile Phones (120) | ○ 1 set of bullets |
| ○ 3 sets of coins | ○ 4 MP3 players | ○ 4 mobile phones | • Scissors (40) |
| • Keys (90) | | • Wristwatches (40) | ○ 1 pair of nail scissors |
| ○ 3 sets of keys | | ○ 1 wristwatch | ○ 1 pair of office scissors |

The data recorded for each walk-through consists of the estimated tensor value, $\bar{\mathbf{M}}$, the residual of the inversion algorithm, r , and the estimated coordinates for the path of the object, \mathbf{P} . The main library, subsequently referred to as '*Main, all*' contains of all the recorded measurements.

A second library, called '*Reduced*', was produced which consisted of a single object per class. This was done to balance the probability of classification, as the outcome of KNN algorithms is known to be dependent upon the number of samples per class. The data consisted of measurements from two different locations, in the left trouser pocket and along the central line of the portal at chest height; these are labelled '*Left pocket*' and '*Chest*'. At each position, 10 scans were performed, resulting in 20 measurements for each object. Thus, the total size of this second library was 200 measurements.

Previous testing with a calibration object has indicated that some tensor components deviate by up to 50% when the same object is scanned in different regions of the portal. Typically this variation occurs as the object trajectory moves from one side panel of the detector to the other. In order to demonstrate this effect and to evaluate the performance of the KNN algorithm in such circumstances, the results from the '*Chest*' and '*Left pocket*' libraries described above have been compared.

Tensor reliability can be estimated from the residual value, r , of the inversion algorithm described in [3]. The residual is calculated by taking the L2-norm of the difference between the actual measurements, ρ , and the forward response as a function of the inverted tensor and 3D coordinates, $\hat{\rho}$, and dividing this value by the L2-norm of the inverted measurements, $\hat{\rho}$; this is defined in (1).

$$r = \frac{\sqrt{\sum_{k=1}^n |\rho_k - \hat{\rho}_k|^2}}{\sum_{k=1}^n |\hat{\rho}_k|^2} \quad (1)$$

Experience has shown that residual values greater than 0.50 indicate unreliable tensors, and that anything in excess of 0.35 can be considered to be a poor representation of the object's tensor. As a result of this observation a further two versions of each library have been created. These have been made by selecting all of the samples that have a residual less than 0.5 and 0.35. The libraries are called ' $X, r < 0.5$ ' and ' $X, r < 0.35$ ' respectively, where X represents the base library name.

A total of ten objects were used to construct the library for investigation of the body effect, five of which were threat objects and the remaining five were innocuous ones. The threat objects were the aluminium and steel NIJ handguns [6] and three knives - *Opinel Lame Acier 12*, the *Opinel Inox 8* and a large kitchen knife with a stainless steel blade.

Two adult candidates of substantially differing heights were used to conduct this experiment. Candidate A had a height of 1.86 m and candidate B had a height of 1.55 m. Each person performed the same number of walkthroughs, 10 for each object, which resulted in 100 measurements per candidate. The object location was chosen to be central with respect to the distance between the side panels, and at chest height of candidate A. The same height was maintained for candidate B, resulting in keeping the object at approximately neck level.

Figure 1 shows a typical response of how the inverted tensors vary with different candidates. The different colours represent the two candidates, and the different markers represent the three different eigenvalues. The two test objects, made of aluminium and stainless steel, in the case shown represent guns. Due to the clustering of the points for each candidate it is believed that the differences correspond to the body effect rather than noise from the inversion algorithm.

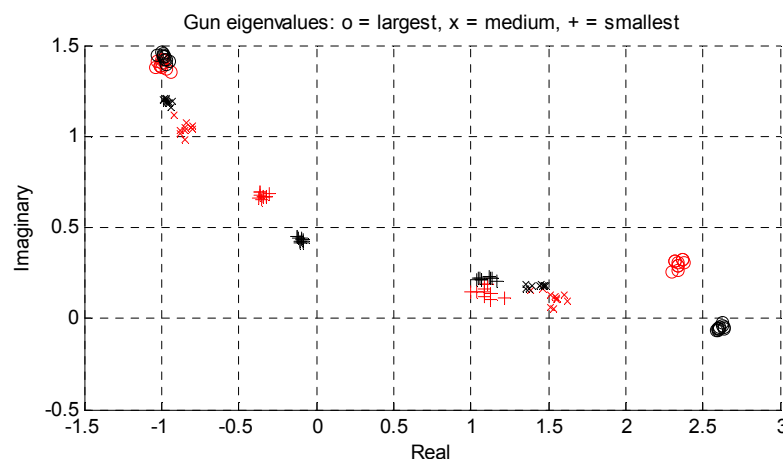


Figure 1. Body effect on eigenvalues

2.2. Implementation of the algorithm

The method is based on the classification algorithm presented in [4]. The magnetic polarisability tensor, \vec{M} , takes the form of a complex, symmetric 3×3 matrix as shown below:

$$\vec{M}(f) = \begin{bmatrix} M_{11} + jN_{11} & M_{12} + jN_{12} & M_{13} + jN_{13} \\ M_{12} + jN_{12} & M_{22} + jN_{22} & M_{23} + jN_{23} \\ M_{13} + jN_{13} & M_{23} + jN_{23} & M_{33} + jN_{33} \end{bmatrix}$$

The algorithm firstly calculates the eigenvalues of the tensor, $\vec{\lambda}$. These eigenvalues are a rotation-invariant representation of \vec{M} . As \vec{M} is complex its eigenvalues form a vector containing three complex values. These three values are then sorted in order of increasing magnitude, $\vec{\lambda}_s$. The magnitude is calculated by multiplying each value by its complex conjugate.

Each object is classified by using (2) to compare the Euclidean distance, D_i between the object's sorted eigenvalues and all of the samples in the library, where the subscript i refers to the library index. The vector of distances is sorted in order of smallest to largest values to produce \vec{S} , and the first K values are selected. The classification outcome, ζ , is calculated by taking the statistical mode, $\text{Mo}()$, of the class of each of the K nearest distances as shown in (3); often K is an odd number to reduce the chances of even numbers of neighbours belonging to different, most popular classes.

$$D_i(\vec{\lambda}_a, \vec{\lambda}_b) = \sqrt{(\lambda_{a1} - \lambda_{b1})^2 + (\lambda_{a2} - \lambda_{b2})^2 + (\lambda_{a3} - \lambda_{b3})^2} \quad (2)$$

$$\zeta = \text{Mo}(\text{Class}\{S_1 \quad \dots \quad S_k\}) \quad (3)$$

The results of the classification are evaluated according to two criteria. Firstly, by the accuracy of determining whether an object is considered to be threatening or innocuous, and secondly, by the accuracy of correctly identifying which of the 10 classes the object belongs to. Normalised values for the latter case have also been calculated to correct for differences in class sizes. This is defined as the average recall for all classes.

False negatives, i.e. classifying an object as innocuous when it is really a threat, are not acceptable in the application area. Therefore, the threat recall score should be 100% while still maintaining an acceptable level of overall accuracy. In a security screening application, this means that all threats are spotted while maintaining a low false alarm rate.

2.3. Limitations of the method

The results presented in this paper consider only situations where a single metallic object is within the detection volume of the portal. The classification algorithm would theoretically perform equally well regardless of how many objects are detected, providing that the quality of all tensors remains the same. The case of multi-object classification remains untested for measured data.

Although the algorithm utilises the tensor approximation (which is location invariant), and tensor eigenvalues (which are rotation invariant), the inversion algorithm is sensitive to certain locations within the detector space and also to variations in orientation as the object passes through the detector. In addition to this, it is known that the orthogonal field components are not of equal magnitude, and that as a result the direction with respect to floor-to-ceiling displacement tends to be noisier. Also, the areas at the very top and very bottom of the detector have a reduced concentration of coils, and consequently the tensor quality decreases in these regions. The effect on the classification outcome can be equated to that of cases with large residual values (typically $r > 0.35$).

As a final point it should be noted that KNN algorithms are highly dependent upon the underlying example library. If the library is not exhaustive, samples that are numerically far away from all of the examples tend to be classified as the class that has the most examples.

3. Results and Discussion

The results of the KNN are shown in Table 1. The algorithm was run once for each library with the parameter value $K=1$. For the library 'Main, all' the algorithm was run also with parameter values $K=3$ and $K=5$. Leave-one-out cross validation was used, unless stated otherwise. The results show that the classifier performance seems to be the best with $K=1$ when the library 'Main, all' is used. This is most likely due to the fact that there are only a few samples from some classes and a large number of samples from others. As discussed previously this is a limitation of KNN.

Table 1. Full results of experiment.

Library	K	Accuracy (%), threat/innoc.	Accuracy (%), class	Accuracy (%), class, norm.	Recall (%), threat
Main, all	1	98.9	97.6	96.0	99.4
	3	98.3	97.1	94.9	99.4
Main, all	5	98.6	96.7	94.1	99.5
Main, R < 0.5	1	99.3	98.9	97.9	99.8
Main, R < 0.35	1	99.5	99.0	97.7	99.7
Chest	1	99.3	97.4	97.4	99.0
Chest, R < 0.5	1	100	99.7	99.8	100
Chest, R < 0.35	1	100	99.4	98.6	100
Left Pocket	1	99.6	96.7	97.2	100
Left Pocket, R < 0.5	1	100	98.1	98.3	100
Left Pocket, R < 0.35	1	100	97.5	97.4	100
Reduced	1	100	98.5	98.5	100
Body Effect, all[^]	1	100	98.5	97.9	100
Body Effect, all[*]	1	96.5	88.0	82.9	100
Candidate A	1	100	100	100	100
Candidate B	1	100	97.0	95.7	100

[^] based on a 'leave-one-out' classification approach

^{*} based on a classification of Candidate A's measurements using Candidate B's library data and vice versa

Table 1 shows that the classifier appears to execute properly with all of the libraries tested. Recall is 99% or higher for all tested libraries; from a practical point of view this value needs to be higher to prevent security breaches, however this could be improved by improving the complexity of the classification algorithm, and also by biasing the threat objects in the library.

The testing with Candidates A and B shows that the body effect seems to be noticeable in classification results. In the results the recall of threat objects remained at the required value of 100%, however the ability to classify the objects fell substantially. Also, there were a greater number of false positive classifications where innocuous objects were misclassified as threats. In the testing, the performance was reduced when the library and test data was swapped such that the library was for Candidate A's data, whilst Candidate B was being scanned, and vice versa.

It can be seen that removing high residual samples generally improves the performance by a noticeable amount, cutting down misclassifications by 36-55%. However, it can be noticed that in some instances the removal of all samples with a residual higher than 0.35 does not improve performance. This is because there are fewer examples of some object classes such as keys and coins that tend to yield noisy tensor values. This causes bias towards the classes with a higher number of examples, and larger items which are more readily detectable.

The results show that, as expected, the classifier performs better when using only data from a single location, e.g. pocket data, instead of using a mixed set of data.

4. Conclusions and Future Work

The results of this study show that the modified KNN algorithm is capable of classifying targets consistently and with a typical normalised accuracy of over 95%, and a recall value of in excess of 99%. Based on this, it is clear that this improvement shows great promise to the field of inductive

metal detection. However, there are a number of improvements that could be made to this algorithm and there is further research which can be conducted which the authors expect would improve the results shown here.

As previously discussed, the KNN approach is a relatively simple algorithm which is subject to several limitations. It is probable that the success of the method reported here could be improved by implementing a more complex algorithm. One way to enhance the method is to use heuristics and the 3D location information of the metallic object that is given by the detector system. For example, if an object was to be classified as a wristwatch, then statistically it is very unlikely that it would be near the floor level. Also, given the variation in tensor components as a function of location within the detector, the location information of the object to be classified could be used to increase the trust in those object samples in the library that have been recorded from the same region of the detector space. An extra level of validation could be added to the algorithm which would take this into account, thereby improving the result.

The results presented in this paper indicate that the detector and classifier are sensitive to substantial changes in the body size of the candidate. Even if samples were to be recorded in the absence of the candidate, e.g. with a robotic arm, there is still a correction that must be made for the body effect. One possible way to reduce this capacitive coupling would be to introduce screening between the coils and the person being measured. Although this paper has shown that the classification remains successful regardless of the contribution of the body effect from the candidate, further study is needed to determine the extent of this effect and how it may be overcome.

Given the strong frequency dependency of the tensor, it is considered that the most significant adaptation which could be made to improve the effectiveness of the classification algorithm would be to use the broadband tensor components rather than those at a fixed frequency; the classification would be fitting a curve rather than a single point. This remains a topic for future research.

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