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Multi-sensor data fusion application for Cargo Screening

A Bayesian approach

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***Abstract*— The challenge of border security agents across the world is to detect contraband before they are smuggled into the country. To help achieve this, different sensors are used to sense for various substances. However, with high rate of false alarms and false negatives, there is need to develop a system to restore operator confidence and improve detection. This paper by simulating sample data, suggests a fusion of data from two sensors using the Bayesian Inference showing an improved and therefore producing a more reliable detection.**

Keywords-multi sensor data fusion, bayesianinference, cargo screening, demster shafer, fuzzy logic

I. INTRODUCTION

Borders are the final points of entry into any country. They could be seaports, airports or land borders. In this report, the term 'border' refers to Land frontiers between independent countries and sea ports.

It is the responsibility of the government of any country therefore to make sure that people and goods entering into the country via the borders meet the requirements set by the laws of the land. Governments of different countries have various agencies in charge of their border control. The Customs and Border Protection Agency is the United States Department of Homeland Security's agency in charge of screening imported cargo entering into the US via more than 300 land, air and sea ports (CBP) [1] while in the United Kingdom, the agency in charge of border security is the United Kingdom Border Agency (UKBA). These agencies work to screen the people and goods entering into the country for contraband. Contraband in this case is defined as goods whose importation is prohibited by law common among which is explosives, drugs, etc.

Goods, brought into the country by ship, airplanes, trains, etc for commercial purposes are known as cargo. These cargo are usually enclosed in metal containers. A container is a metallic box used as a means of storage of goods from place to place (fig 1). A typical container is either 20 foot or 40 foot long. The industry standard reference is the Twenty foot Equivalent Unit (TEU) and the most commonly used container size now is the 40 foot also known as the 2 TEU [3].

fig1 a typical container [2].

II. BACKGOUND

A. Cargo Screening

The focus of this paper is to review the different methods of screening cargo entering into the UK via the land borders and to introduce a new technique of screening these cargos.

The United kingdom land and sea borders have about 9,000 staff working for the UKBA [4]. This staff is responsible for detecting contrabands at all UK borders which may include illegal drugs, explosives, and even large quantities of cigarettes which though may be allowed in small quantities but are illegal in large quantities. Some smugglers try to bring them in by hiding them in between other legal goods in containers. Mostly this is done to evade tax.

According to the UK Drug Policy Commission (UKDPC), drug trafficking poses the single greatest threat to the UK [5] with the UK Cabinet office [6] estimating that about £15.4 billion per year is lost to organised crime such as drug trafficking.

With the above in view, it can be seen that the danger posed by illegal importation of contrabands cannot be over emphasized with smugglers even now extending to attempting to smuggle in multi consignment contraband (MCC). Multiple Consignment Contraband (MCC) smuggling is defined as two or more different types of contraband smuggled at the same time [7].

It is therefore important that these contrabands are detected and seized at points of entry.

B. Current Screening Techniques

Current screening techniques can be grouped into imaging and non imaging.

The imaging techniques include the X-ray, Gamma ray and Neutron technologies. The X-ray machines installed at sea borders and are specifically tailored for the inspection of containers, trucks and rail cars within small confined areas [8]. Two primary components responsible for determining the quality of an x-ray image are 1. The source having enough power and dose to fully penetrate densely loaded container and yet not too much power to result in excessive cost, size and operating area space requirements and 2. The detector array must be highly sensitive and possess a wide dynamic range to provide data that accurately reflects the object being scanned. Selectivity of materials that can be scanned is a major impediment against the use of x-ray scanning machines. The challenge for X-ray technology is in its ability to maintain a balance of being dense enough to penetrate the densest cargo while not being dense enough to cause health issues. There is also a challenge of image quality. Though effective in determining the contents of a container,

Gamma ray technology have lower radiation field when compared to similar X-ray technology thus providing a smaller safety exclusion zone [9].

Another imagine technique, the Neutron system creates gamma-ray signals when it interacts with the elemental ingredients of the inspected object. The gamma-ray energies are unique to the elements in the inspected object. If the gamma-ray signatures match those in a threat database, the system automatically alarms indicating the possible presence of the threat.

In all, Imaging technology depends much on the quality of the image and the penetration of the rays used. The down side however, is in their size. Figure 2a and 2b below shows X-ray machines used at various borders. The use of highly dangerous radioactive materials also makes it important that a safety exclusion zone must be created when the system is in use. Thus adding to the already large space needed.

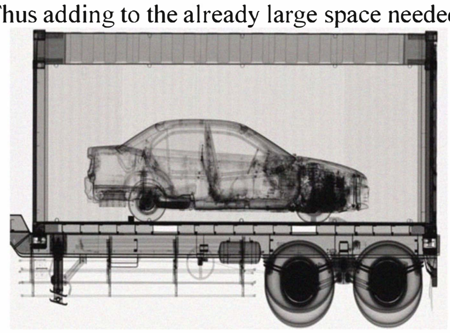

fig2a image from an x-ray scanner

fig 2b x-ray scanner inspecting a truck

Non imaging techniques like the name suggests depends on other methods outside imaging to detect for contraband. Examples include Gamma backscatter, radio activity detectors, metal detectors, and dogs.

In the case of dogs for instance, in the United Kingdom, a significant expansion in the use of police drug detection dogs took place in the late nineties/early 21st century [10]. Dogs have the advantage of being able to detect odours undetectable by human senses [11]. These dogs scent individuals and luggage as they pass through security at borders and give off an alarm by barking whenever it detects a scent that matches the scent he is trained to detect.

As well as the search dogs, UKBA staff use carbon monoxide probes which can tell if people are breathing out in the back of a lorry. They also use "heartbeat detectors" which can detect the tiniest movements.

The challenges here are a bit obvious. Dogs and human detectors can get tired and thus less careful at some stage. Repetition of same duty could lead also to boredom leading to the same consequence. This will increase the false negatives, allowing illegal substances going undetected.

III. MULTI-SENSOR DATA FUSION

Multi sensor data fusion seeks to combine data from multiple sensors in making inferences which are not possible from a single sensor perspective [12]. The concept of data fusion itself is likened to the way the human and other biological systems function. By combining 'data' (sight, sound, scent and touch) from the body's sensors (eyes, ears, nose, fingers) added to prior knowledge to assess events going on around, the system is able to detect, analyse and understand the world around him. Multi-sensor data fusion seeks to mimic this system [13].

Applications of data fusion varies from military (automatic target tracking, analysis of battle field situations, threat assessments), remote sensing and robotics (robot vision and positioning). This report seeks to extend the application of multi sensor data fusion to cargo screening.

Characteristics of some sensors show that they can detect different targets with varying detection probabilities. For example, a sensor that tests for the presence of cocaine in a container may also detect the presence of other substances that have almost the same signature as cocaine such as ketamine, codeine, etc. it is therefore a problem to correctly state that there is a presence of cocaine in that substance. However, fusion systems use techniques to analyse and combine these incomplete data and eventually making conclusions and giving more reliable results with lower false alarms and higher detection rates than when a single set of sensor data is used.

Three techniques investigated for the purpose of this research are – Bayesian Inference, Dempster-Shafer and Fuzzy Logic. This paper discusses the Bayesian, and subsequent follow up papers will discuss the other techniques.

A. Bayesian Inference

Bayesian Inference

The Bayes theorem was first proposed by English Clergyman, Thomas Bayes, in a 1763 paper [14]. The Bayesian Inference updates the likelihood of a hypothesis given a previous likelihood estimate and additional observations [12]. In simple terms, the inference helps to use the current known information (observed data) and the initial background information (a priori) to infer the future (posterior). Mathematically,given that the probability of two events occurring i.e.

$$p(A,B) = p(A|B)*p(B) \quad (1)$$

and

$$p(A,B) = p(B,A) \quad (2)$$

then

$$\boldsymbol{p(A|B) = p(B|A)*p(A) / p(B)} \quad (3)$$

(3) above is known as the Bayesian Inference and is the basis of many fusion processes.

IV. CARGO SCREENING AND BAYESIAN DATA FUSION

In this research, Bayesian inference as analysed above will be used in fusing data from two sensors. The background of the research is based on the development of two sensors (or one sensor) testing for the presence of a particular type of drug in an environment (e.g. cargo). One of these sensors is already being developed [15]. The sensors primarily detect the presence of cocaine but also detect other substances – ketamine, amphetamine sulphate, ecgonine methyl ester and buprenorphine.

Now, data can be fused in several ways – centralised fusion which combines all of the raw data from the sensors in one main processor or the data at each sensor can be pre-processed before being fused at the processor [16]. The advantage of the latter over the former is that the former tends to consume a lot of computing power since a large amount of data transverses the network. However, with the latter, since data is pre-processed at each sensor, it reduces the amount of data flow needed and consequently, lesser computing needs. The figure below shows three of the several ways sensors can be fused. The third method shown is a hybrid of the first two.

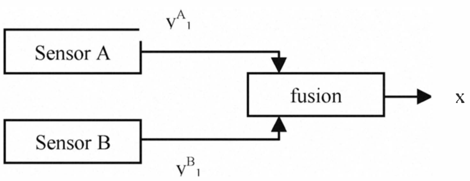

fig 3a. Centralized data fusion

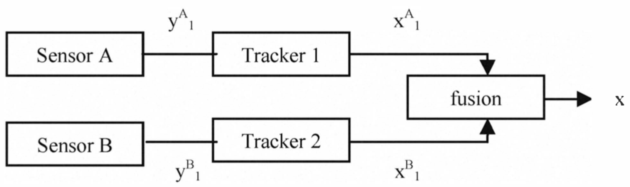

fig 3b centralized fusion with preprocessing done at each sensor

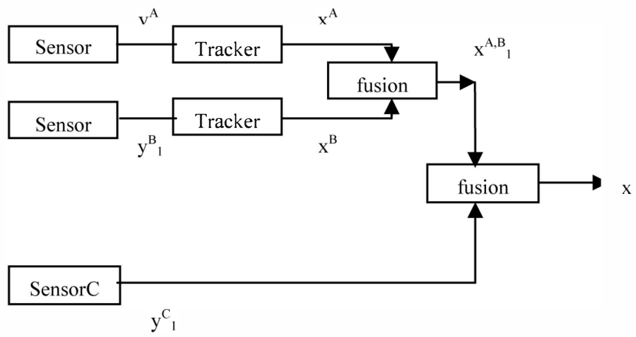

fig 3c hybrid of 3a and 3b

fig 3 fusion of multiple sensors [16]

For this case of cargo screening, consider two sensors A and B, each sensor observing the inside of a cargo container and whose signatures indicate the presence of one of three banned drugs – alpha, beta or gamma.

From figures 3b above, the first step is to track the target using each of the two sensors. The sensors make observations at intervals and if we define the following terms:

If both sensors collect two sets of data sequentially (i.e. sensors A and B collect data at 'time' 0 and 1)

x_1 *as the state of the target at 'time' 1 (present time for single iteration)*

y^A_1 *is the observation made of target at 'time' 1 by sensor A*
y^B_1 *is the observation made of target at 'time' 1 by sensor B*
Y^A_0 *is set of old data collected by sensor A*
Y^B_0 *is set of old data collected by sensor B*
Y^A_1 *is set of all observations made of the target by sensor A up to present time*
Y^B_1 *is set of all observations made of the target by sensor B up to present time*

N.B: $Y_1 = Y_0 + y_1$ for both sensors.

Then the new estimate of the target state $p(x|Y_1)$ given old estimate $p(x|Y_0)$ is,

$$p(x_1|Y_1) = p(y_1|x_1) * p(x_1|Y_0) / p(y_1|Y_0) \quad (4)$$

where $p(y_1|x_1)$ is the likelihood and $p(x_1|Y_0)$ is the predicted density which can be further expanded using the Chapman-Kolmogorov identity and assuming the current state of the system depends only on its previous state with all old measurements encapsulated in the previous state, to give

$$p(x_1|Y_0) = \int dx_0\, p(x_1|x_0)*p(x_0|Y_0) \quad (5)$$

$p(x_0|Y_0)$ in (5) above is the prior probability and can also be the result from previous iteration (if current iteration is >= 2).

Finally from (4) above, $p(y_1|Y_0)$ is used to normalizing the numerator and can also be expanded using the Chapman-Kolmogorov identity to give –

$$p(y_1|Y_0) = \int dx_1\, p(y_1|x_1) * p(x_1|Y_0) \quad (6)$$

(4) above is the probability of the target state at the present time given up to date set of all observations made of the target. This result gives what contraband from alpha, beta or gamma each of the two sensors believes has been detected.

The next stage involves fusing the results from the above using the Bayesian inference ((3) above). Using the same notations, the probability of both sensors detecting a contraband, x is thus,

$$p(x|Y^A{}_1Y^B{}_1) = p(x|y^A{}_1y^B{}_1Y^A{}_0Y^B{}_0) \quad (7)$$

and using Bayes rule,

$$p(y^A{}_1y^B{}_1|x, Y^A{}_0Y^B{}_0) \,/\, p(y^A{}_1y^B{}_1|Y^A{}_0Y^B{}_0) \quad (8)$$

Assuming the sensor measurements are independent and implementing Bayes rule once again, fusion of the data from the two sensors is given as,

$$p(x{=}alpha|Y^A{}_1Y^B{}_1)= p(x{=}alpha|Y^A{}_1)*p(x{=}alpha|Y^B{}_1)*p(x{=}alpha|Y^A{}_0Y^B{}_0) \,/\, p(x{=}alpha|Y^A{}_0) * p(x{=}alpha|Y^B{}_0) \quad (9a)$$

$$p(x{=}beta|Y^A{}_1Y^B{}_1)= p(x{=}beta|Y^A{}_1)*p(x{=}beta|Y^B{}_1)*p(x{=}beta|Y^A{}_0Y^B{}_0)/ p(x{=}beta|Y^A{}_0) * p(x{=}beta|Y^B{}_0) \quad (9b)$$

$$p(x{=}gamma|Y^A{}_1Y^B{}_1)= p(x{=}gamma|Y^A{}_1)*p(x{=}gamma|Y^B{}_1)*p(x{=}gamma|Y^A{}_0Y^B{}_0)/ p(x{=}gamma|Y^A{}_0) * p(x{=}gamma|Y^B{}_0) \quad (9c)$$

each of the value above is then multiplied by the normalisation factor (usually the inverse of the sum of 9a, 9b and 9c). As can be seen, the individual sensor probabilities $p(x|Y^1{}_1)$ and $p(x|Y^2{}_1)$ have been fused to update the prior probability (or posterior probability from previous iteration) to give the results in 9a, 9b and 9 c above. The probability with the highest numerical value from 9a, 9b and 9c after normalization is the target most likely detected.

[16] has shown that the above can be extended for situations where there are more than two sensors in which case, for a three sensor system, we will have

$$p(x|Y^A{}_1Y^B{}_1Y^C{}_1) = p(x|Y^A{}_1)*p(x|Y^B{}_1)*p(x|Y^C{}_1)*p(x|Y^A{}_0Y^B{}_0Y^C{}_0) \,/\, p(x|Y^A{}_0)*p(x|Y^B{}_0)*p(x|Y^C{}_0) \quad (10)$$

multiplied by the normalization factor.

The probabilities $p(x_0|Y_0)$ and $p(x|Y^A{}_0Y^B{}_0)$ are prior probabilities of the tracking and fusion processes. If more than one iteration is performed, the prior is the posterior probability calculated for the previous iteration. However, for the initial iteration, the operator is allowed to input the prior into the system based on his judgement. In this case, several factors come into play including the origin of the container. Already, this method is being used at various ports (visited by the writer) where the decision on whether to search or not search a container is partly based on prior information known about the country of origin and/or company or individual shipping in the cargo. However, if there is insufficient knowledge about the container, prior probabilities can be set equally (principle of indifference).

V. EXPERIMENT

A. Implementation Results

This model was implemented with the MATLAB software. Two sensors are simulated in this case. Each sensor with the ability to detect three contrabands i.e. substance1, substance2 and substance3. The technique used for this model is explicitly described for another application in [16]. Fig4 shows data By generating data following a Normal distribution representing both target and non target data sets with an arbitrary threshold (fig 4) to represent contaminated and non contaminated environment. Data above the threshold could either be a false alarm or a true positive and the likelihood probability is computed. The priors were selected in this case randomly (in the real life scenario, initial priors are selected based on information known about the received cargo and are entered by the operator).

The algorithm involves two stages – 1. Tracking of sensor data per individual sensor. This can be viewed as fusion over time In the real life implementation, two sets of data will be collected over time. This was simulated by generating two sets of data (YA0 and y1) and calculating for their likelihood and predicted density probabilities. Simulated results from tracking for each sensor (using (4) above) is shown in table 1 below.

Sensor 1($Y^A{}_0$)	**Sensor 2 $Y^B{}_0$**
P(substance1 | $Y^A{}_0$) = **0.4**	P(substance1 | $Y^B{}_0$) = **0.5**
P(substance2 | $Y^A{}_0$) = **0.3**	P(substance1 | $Y^B{}_0$) = **0.3**
P(substance3 | $Y^A{}_0$) = **0.3**	P(substance1 | $Y^B{}_0$) = **0.2**
Sensor 2($Y^A{}_1$)	**Sensor 2($Y^B{}_1$)**
P(substance1 | $Y^A{}_1$) = **0.64**	P(substance1 | $Y^B{}_1$) = **0.76**
P(substance2 | $Y^A{}_1$) = **0.22**	P(substance2 | $Y^B{}_1$) = **0.21**
P(substance3 | $Y^A{}_1$) = **0.14**	P(substance3 | $Y^B{}_1$) = **0.03**

Table1. Step 1 tracking probabilities from sensors 1 and 2.

The second step involves fusion of data from both sensors. Using equations 9a, 9b and 9c. The priors in this first step fusion iteration in 9(a,b and c) above is determined by the operator of the system and are values ranging from 0 and 1 which are based on the history and origin of the container received. The summation of all priors must be unity. For subsequent iterations, the result from this fusion becomes the prior probabilities P(substanceX | $Y^A_0 Y^B_0$), **where X is 1,2 or 3.** For this experiment, initial priors are arbitrary as 0.5, 0.3 and 0.2 for P(substance1 | $Y^A_0 Y^B_0$), P(substance2 | $Y^A_0 Y^B_0$) and P(substance3 | $Y^A_0 Y^B_0$) respectively.

Fusing using eqn and applying the priors gives

P(substance1) = 1.216

P(substance2) = 0.154

P(substance3) = 0.014

Applying the normalization factor, gives

$p(x=substance1|Y^A_1,Y^B_1) = 87.9\%$

$p(x=substance3|Y^A_1,Y^B_1) = 11.1\%$

$p(x=substance3|Y^A_1,Y^B_1) = 1.0\%$

This result indicates that the substance detected is most likely substance1.

VI. CONCLUSION

The aim of this report is to highlight the menace caused by smugglers at borders and show the shortcomings of current detection techniques which are mainly single based and are prone to errors while introducing a new approach to contraband detection in Cargo Screening.

Most cargo imported into the country is brought in via containers. Smugglers use the opportunity that the containers are sealed to smuggle in contraband into the country. Current detection methods are time consuming and give a high false positive which results in loss of operator confidence and worse still, false negatives.

By applying the concept of multi-sensor data fusion application of fusing data from two sensors, results are expected to improve. We have demonstrated the ways by which Bayesian inference can be applied to this fusion given two or more sensors detecting for various substances in a container.

The Bayesian inference allows the likelihood probabilities from multiple sensors to be fused to give a single result which should give more improved information in terms of reduction in false positive and false negative detections in the environment under review.

The major challenge with the Bayesian inference is the use of priors. In this case, it is an advantage as the operator is allowed input into the performance of the system by setting the prior values of the fusion process based on previous knowledge of the source of the container.

This research is an on going work and subsequent papers will show other fusion techniques mentioned in section III above.

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