DECISION SUPPORT SYSTEM ARCHITECTURE FOR THREAT OBJECT DETECTION IN DEFENCE ENVIRONMENTS

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***Abstract*—Detection of threat objects such as Improvised Explosive Devices (IEDs) has become a serious challenge in defence environments. Currently a number of individual technology sensor systems are used to detect different aspects of these threat objects. In complex scenarios, human operators are challenged to interpret multiple sensor outputs in real time. This includes making decisions about the nature of the threat encountered and taking appropriate action.**

This paper presents a novel decision support framework to assist human operators in making decisions through fusion of outputs from multiple sensors with the situational awareness information available at the time.

Keywords—computational intelligence, improvised threat devices, anomaly detection, data fusion

I. INTRODUCTION

Detection of threat objects has become a serious challenge in defence and national security environments. Currently a number of individual sensor systems are being used to detect different aspects of these threat objects [1]. Due to the evolving nature of threat objects and their concealment techniques, there are a growing number and types of sensors required to detect different aspects of threat objects.

Due to the rapid increase in insurgent related activities, countering the on- and off- route threats such as landmines and IEDs has become a priority in Defence and National Security environments. Landmines and IEDs are extremely diverse in design and may contain many types of initiators, detonators, casing materials and explosive loads. A variety of sensor technology including acoustic, chemical, electromagnetic, hyper-spectral sensors, Ground Penetrating Radar (GPR), and electro-optical sensors have been employed to detect different aspects of landmines and IEDs [2].

Typically these are incorporated into multi-sensor platforms with human operators. In these systems, the human operators are challenged to correctly identify the nature of the threat objects based on multiple individual sensor outputs and then choose an appropriate course of actions. In most of the operational scenarios, this decision making process needs to be completed in real time or under strict time constraints. In some complex situations, the operator may also need to change their decision based on the introduction of further intelligence data. Due to the ever increasing complexity of this task there is a need for an intelligent Decision Support System (DSS) to assist human operators to make decisions based on all available data sources efficiently. Although a large body of research has been carried out on DSS's, it is often difficult to apply the inventory of various decision support techniques to solving for specific applications [3]. This paper presents a DSS framework to assist operators to make decisions based on outputs from multiple sensors combined with the situational awareness information available at the time in landmine/IED detection scenarios.

II. DECISION SUPPORT SYSTEM ARCHITECTURE

Fig. 1 shows a schematic diagram of the proposed multi-input DSS for multi-sensor platforms, used for landmine/IED detection. When multi-sensor platforms are in operation, individual sensors detect different aspects of anomalies in a common geo-located area.

Raw data outputs from each sensor are directly passed to separate data "Pre-processing and Feature Extraction" (PFE) modules. This output data is processed to detect subsurface anomalies. When subsurface anomalies are detected the relevant data are further processed to extract features of the suspected target using real-time signal processing algorithms embedded within each module. For example, metal detectors and GPR can be used to determine physical properties of subsurface anomalies such as the metal content, metal type, burial depth, target size and its dielectrics properties [1, 4]. Sensors such as visible spectrum and Infrared (IR) cameras provide visual clues such as disturbed soil conditions of suspected threat locations [5]. Once feature extraction is complete these features including their time and geo-location stamps are passed to the "Information Fusion" module.

The role of the Information Fusion module is to characterise each subsurface anomaly by associating all available features with potential threat target types. Input to this module is individual feature sets from single sensors, which in turn are used to produce a Combined Feature Vector (CFV) formed by consolidating all information acquired by multiple sensors for a particular threat.

The CFV representing the full set of features for the threat object is then passed to the "Target Type Determination" module for matching the feature vector with the most probable target type. Potential types of threat objects or clutter can be considered as hypotheses h_1, h_2, ..., h_n. Each hypothesis h_j will have a certain probability to occur. The Target Type

Determination module generates a vector containing the likelihood of each potential target occurring. The best decision is inferred on the basis of the estimated cost of the consequences of the options being considered.

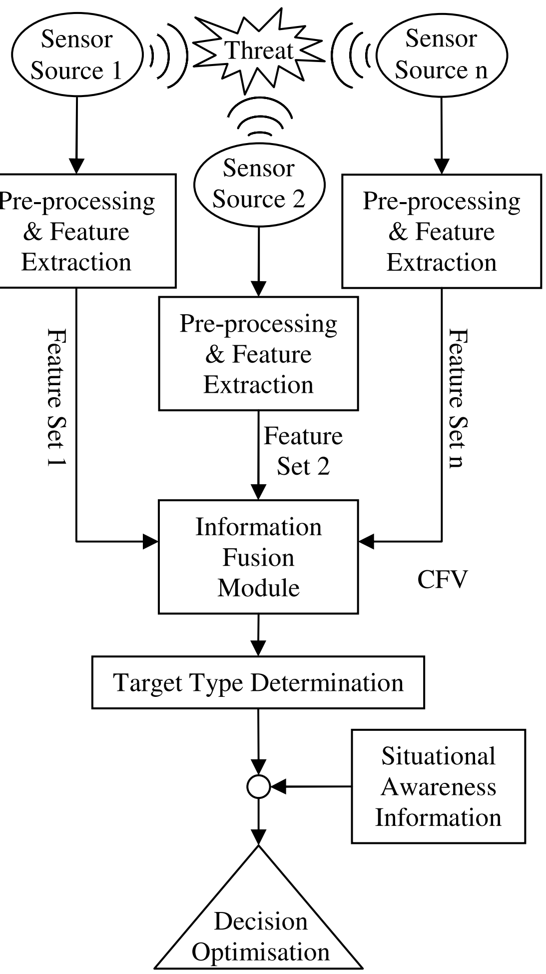

Fig. 1. Schematic diagram of the proposed multi-input decision support system.

The final "Decision Optimisation" module updates the likelihood values of occurrence for each threat type by incorporating the latest situational awareness information available at the time in addition to sensor readings. This module provides flexibility to incorporate any timely intelligence passed on to the operator in addition to sensor readings before making a decision about the threat encountered, and subsequently choose a course of action.

A. *Pre-processing and Feature Extraction Module*

In demining and IED detection operations multiple sensor kits mounted on vehicle born platforms are used to detect subsurface anomalies, and to discriminate threats from clutter objects [2,6].

Initially, the main features of suspected threat objects are extracted by pre-processing the output data (alarm signals) acquired from individual sensors. For this analysis, we employ a CFV, which is populated by consolidating the feature sets from individual sensors, ensuring they are geospatially co-located with the same area in the suspected threat object. Standard signal processing based feature extraction techniques can be implemented to extract physical properties of suspected threat objects from the output data of individual sensors [7].

B. *Fuzzy Logic based Target Type Determination Module*

The role of this module is to associate the CFV representing the suspected threat object to one of the predefined threat objects. For example, the threat object could be a target or clutter. Definition of threats and clutter is carried out by experts combining relevant features associated with those particular target types.

Unlike standard data fusion methods that operate by fusing local decisions taken by Automatic Target Recognition (ATR) embedded with individual sensors, this method operates at a higher level. The feature vector, generated by consolidating all individual sensor outputs, is associated with categories of potential threat objects and clutter as shown in Fig. 2. At the end of this process, a likelihood value will have been determined for each threat category by matching individual features ($F_1, F_2, \ldots, F_n$) against each target type ($T_1, T_2, \ldots, T_n$). For example, certain types of threat objects can be identified as having a certain size, metal content and burial depth.

However, due to variation of physical characteristics of threat objects it is difficult to associate an exact numerical value to features in each target type or category. In addition, depending on the sensor or equipment type and its data processing methodology, some features may be defined with a degree of uncertainty.

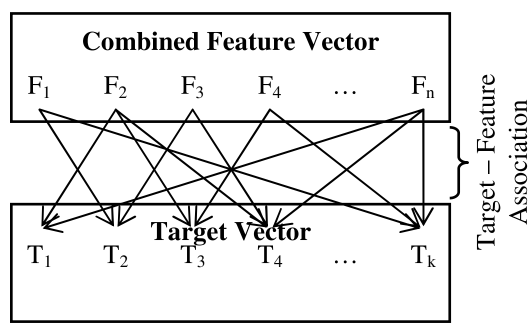

Fig. 2. Association of features with pre-defined target types.

Fuzzy logic is a suitable way to handle imprecise data. Fuzzy logic is based on the idea that all things partially belong to multiple groups or sets. For example, experimentally derived values for features, such as target size and burial depth, can be represented as members of relevant Fuzzy sets rather than limiting them to exact numerical values [9].

The proposed Fuzzy logic based target discrimination framework can be used to assist with associating the combined feature vector (input to the Fuzzy system) against pre-defined target sets (output of the Fuzzy system). This Fuzzy logic-based expert system has three key steps: defining Fuzzy sets for input and output variables, construction of a knowledge base in the form of Fuzzy rules, and inference.

1) *Defining Fuzzy Sets*

Depending on the sensor type and data processing techniques used for pre-processing the individual sensor output data, target features (Fuzzy system) can be represented in the form of crisp or membership functions for linguistic variables. The crisp variable is always a numerical value limited to the universe of discourse, while some of the features can be only expressed in linguistic terms. For example, for a vehicle-mounted multi-sensor landmine detection system the crisp features may include the size and burial depth of the suspected threat object. The linguistic variable may be used to describe target features such as the metal content (e.g. metallic or non-metallic) or shape (e.g. circular, rectangular).

In order to represent input data relevant to any chosen variable as Fuzzy sets, membership functions must be determined.

For example, the size (e.g. radius) of a suspected target (S) ranges from 0 to 100 cm. This range can be represented through Fuzzy sets Small (S_1), Medium (S_2) and Large (S_3) with Fuzzy boundaries as shown in Fig. 3.

Another category of input/output variables is best represented in the form of a Fuzzy singleton, which has a membership function of unity at a particular point in the universe of discourse and zero everywhere else.

2) *Knowledge Base Representation through Fuzzy Rules*

Fuzzy rules provide a framework to analyse complex systems. They map the input space to the output space, and represent knowledge or expert advice.

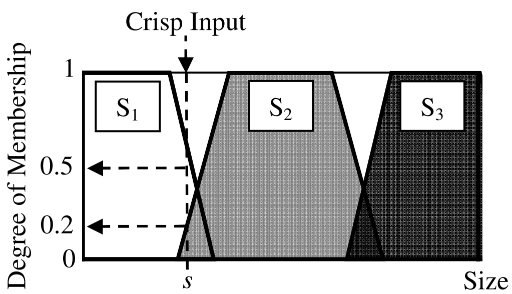

Fig. 3. Example Fuzzy membership function for target size.

After evaluating each relevant Fuzzy rule, a confidence value, C, is generated against each relevant target type as shown in Table 1. Here, let Table 1 represent an example dataset where the rows (R's) and columns (T's) represent Fuzzy rules and target types respectively. An example how the confidence value for each target type is determined as a result of evaluating the relevant Fuzzy rule is shown in Figure4. In this example s is the numerical value representing size and m is represents the metal content.

The decision on the confidence value is determined by summing all likelihood values for each target type and normalising them, as shown in the last row of Table 1. These values are passed on to the decision optimisation module as confidence values for each target type.

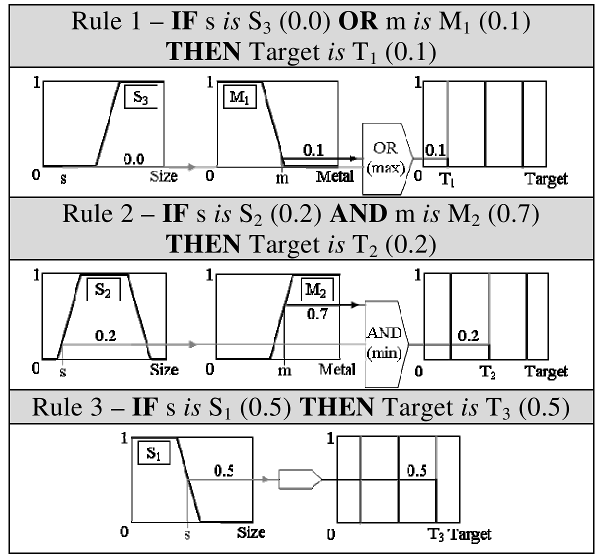

Fig. 4. Fuzzy rule evaluation example.

TABLE I. CONFIDENCE VALUES FOR EACH RULE WITH RESPECT TO TARGET TYPE

	T_1	T_2	…	T_j
R_1	C_{11}	C_{12}	…	C_{1j}
R_2	C_{21}	C_{22}	…	C_{2j}
:	:	:	…	:
R_i	C_{i1}	C_{i2}	…	C_{ij}
Total Confidence	$\frac{\sum_{x=1}^{i} C_{x1}}{\sum_{y=1}^{j}\sum_{x=1}^{i} C_{xy}}$	$\frac{\sum_{x=1}^{i} C_{x2}}{\sum_{y=1}^{j}\sum_{x=1}^{i} C_{xy}}$	…	$\frac{\sum_{x=1}^{i} C_{xj}}{\sum_{y=1}^{j}\sum_{x=1}^{i} C_{xy}}$

III. DECISION OPTIMISATION

The decision optimisation method is aimed at providing the operator with the best advice to take appropriate action under given circumstances. The consequence of any decision taken by the operator will incur costs in terms of time, resources, or even risk of human life, depending on the severity of the situation.

The cost of consequence of the decision for any target type as the threat object depends on the target types associated with the decision. For example, the expected cost incurred when an anti-tank mine is misclassified as a clutter object may be different to a situation when an anti-personnel mine is misclassified as a clutter object. The expected cost for selecting (deciding) target type T_i when the actual target type is T_j can be represented as u_{ij}. However in reality the potential target types can be referred to as hypotheses with each target type T_j having a particular probability P_j of being present at the time. The actual cost for deciding for T_i when T_j is present can be presented as $u_{ij} \times P_j$.

Table 2 summarises the costs matrix associated with various combinations of decisions (D_i when deciding T_i) and actual target types (T_j), and the likelihood for any target type being present.

The rationale behind the decision optimisation is to minimise the cost by taking the decision on the correct target type. The assessment criteria for the decision are formulated as the overall expectation of costs associated with the i^{th} decision (7):

$$E(U_i) = \sum_{j=1}^{n} u_{ij} p(T_j) \tag{7}$$

where $p(T_j)$ is the prior probability for target T_j

The decision on the target type is made on the basis of the least estimated cost and can be represented as (8):

$$E(U) = \min_i E(U_i) \tag{8}$$

At any time situational awareness may lead to an updated vector of target data, through sensor updates or any other communication channel. Real-time information updates can be represented as a vector (9):

$$V = \{v_1, v_2, \ldots, v_t\} \tag{9}$$

Some of the elements of this vector may have an effect on certain types of targets. Each vector element is used to update the probabilities for the full range of threats. This means the prior probabilities against each threat type, delivered as the output of the Fuzzy inference process, will be updated to generate a vector of posterior probabilities.

The updated likelihood value for target type T_j due to the new information v_t can be represented as $p(v_t|T_j)$. These likelihood values are then used as weights to update the existing probabilities of each target type $p(T_j)$ to compute the updated probability (posterior probability)(10):

$$p(T_j \mid v_t) = \frac{p(v_t \mid T_j) p(T_j)}{p(v_t)} \tag{10}$$

where $p(v_t) = \sum_{i=1}^{n} p(v_t \mid T_j) p(T_j)$.

The decision for the updated situation will then be determined as before (11):

$$E(U^*) = \min_i E(U_i \mid v) \tag{11}$$

where $E(U_i \mid v) = \sum_{j=1}^{n} u_{ij} p(t_i \mid v)$.

TABLE II. COST MATRIX

A Priori Probability	**P_1**	**P_2**	**P_3**	**…**	**P_j**
Target Type (T_x) Decision (D_x)	**T_1**	**T_2**	**T_3**	**…**	**T_j**
D_1	u_{11}	u_{12}	u_{13}	…	u_{1j}
D_2	u_{21}	u_{22}	u_{23}	…	u_{2j}
D_3	u_{31}	u_{32}	u_{33}	…	u_{3j}
:	:	:	:	:	:
D_i	u_{i1}	u_{i2}	u_{i3}	…	u_{4j}

IV. CONCLUSIONS

Complex intelligence inferences may be based on masses of information, of different kinds, from different sources.

This paper proposes a new DSS that takes into account the value or utility of decision consequences and the probability of these consequences. The system utilises simplified methods for assessing both value and probability judgements, and a simplified method for combining these judgements in the selection of a course of action.

This paper contributes to a new computing paradigm to bridge the gap between the human user and computer systems. This new methodology can be applied to real world decision processes that involve advanced technology solutions combined with intelligence.

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