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Fuzzy Sets and Rough Sets for Scenario Modelling and Analysis*

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Abstract. Both fuzzy set theory and rough set theory play an important role in data-driven, systems modelling and analysis. They have been successfully applied to building various intelligent decision support systems (amongst many others). This paper presents an integrated utilisation of some recent advances in these theories for detection and prevention of serious crime (e.g. terrorism). It is shown that the use of these advanced theories offers an effective means for the generation and assessment of plausible scenarios which can each provide an explanation for the given intelligence data. The resulting systems have the potential to facilitate rapid response in devising and deploying preventive measures. The paper also suggests a number of important further challenges in consolidating and refining such systems.

1 Introduction

Solving complex real-world problems often requires timely and intelligent decision-making, through analysis of a large volume of information. For example, in the wake of terrorist atrocities such as September 11, 2001, and July 7, 2005, intelligence experts have commented that the failure in the detection of terrorist activity is not necessarily due to lack of data, but to difficulty in relating and interpreting the available intelligence on time. Thus, an important and emerging area of research is the development of decision support systems that will help to establish so-called situational awareness: a deeper understanding of how the available data is related and whether or not it represents a threat.

Most criminal and terrorist organisations are embedded within legitimate society and remain secrete. However, organised crime and terrorist activity does leave a trail of information, such as captured communications and forensic evidence, which can be collected by police and security services. Whilst experienced intelligence analysts can suggest plausible scenarios, the amount of intelligence data possibly relevant may well be overwhelming for human examination. Hypothetical (re-)construction of the activities that may have generated the intelligence data obtained, therefore, presents an important and challenging research topic for crime prevention and detection.

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This paper presents a knowledge-based framework for the development of such systems, to assist (but not to replace) intelligence analysts in identifying plausible scenarios of criminal or terrorist activity, and in assessing the reliability, risk and urgency of generated hypotheses. In particular, it introduces an integrated use of some recent advances in fuzzy set [34] and rough set [23, 24] theories to build intelligent systems for the monitoring and interpretation of intelligence data. Here, integration of fuzzy and rough techniques does not necessarily imply a direct combination of both, but utilising them within a common framework. It differs from the conventional hybridisation approaches [20, 21, 26], although part of the work does involve the employment of the combined fuzzy-rough set theory [3, 9].

The rest of the paper is organised as follows. Section 2 outlines the underlying approach adopted and describes the essential components of such a system. Section 3 shows particular instantiations of the techniques used to implement the key components of this framework. Essential ideas are illustrated with some simple examples. Section 4 summarises the paper and points out important further research. Due to space limit, this paper concentrates on the introduction of the underlying conceptual approaches adopted, with specific technical and application details omitted (which can be found in the references).

2 Plausible Scenario-based Approach

In order to devise a robust monitoring system that is capable of identifying many variations on a given type of terrorist activity, this work employs a model-based approach to scenario generation [28]. The knowledge base of such a system consists of generic and reusable component parts of plausible scenarios, called model or scenario fragments (interchangeably). Such fragments include: types of (human and material) resources required for certain classes of organised criminal/terrorist activity, ways in which such resources can be acquired and organised, and forms of evidence that may be obtained or generated (e.g. from intelligence databases) when given certain scenarios.

Note that conventional knowledge-based systems (for instance, rule or case-based) have useful applications in the crime detection area. However, their scope is restricted to either the situations foreseen or those resulting from previously encountered cases. Yet, organised terrorist activity tends to be unique, whilst employing a relatively restricted set of methods (e.g. suicide bombing or bomb threats in public places). A model-based reasoner designed to (re-)construct likely scenarios from available evidence, as combinations of instantiated scenario fragments, seems to be ideally suited to cope with the variety of scenarios that may be encountered. Indeed, the main strength of model-based reasoning is its adaptability to scenarios that are previously unseen [13].

Figure 1 shows the general architecture of the approach taken in this research. Based on intelligence data gathered, the scenario generation mechanism instantiates and retrieves any relevant model fragments from the library of generic scenario fragments, and combines such fragments to form plausible explanations for the data. A description of how such a system is built is given below.

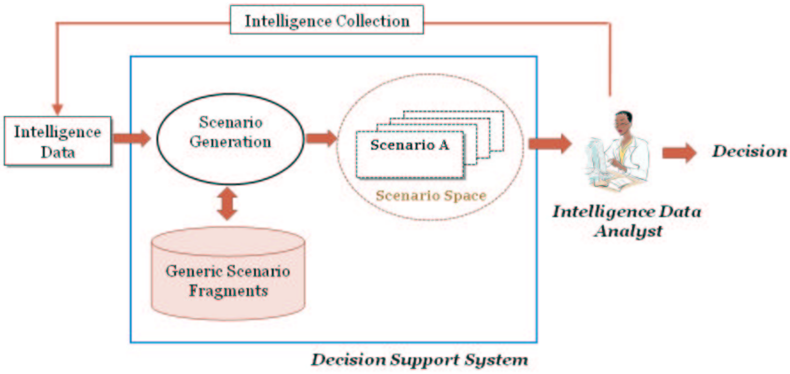

Fig. 1. Architecture of Intelligent Systems for Intelligence Data Analysis

2.1 Flexible Composition Modelling

The central idea is to establish an inference mechanism that can instantiate and then dynamically compose generic model fragments into scenario descriptions, which are plausible and may explain the available data (or evidence). A compositional modelling approach [12] is devised for this purpose. The main potential of using this approach over conventional techniques is its ability to automatically construct many variations of a given type of scenario from a relatively small knowledge base, by combining reusable model fragments on the fly. This ensures the robustness required for the resulting system to tackle the problems at hand.

The compositional modelling approach developed in this research differs from those in the literature in two distinct ways:

1. *Ability* to speculate about plausible relations between different cases. Often, intelligence data will refer to individuals and objects whose identity is only partially specified. For example, when a person is observed on a CCTV camera, some identifying information can be collected, but this may be insufficient for an exact identification. When a person with similar features has been identified elsewhere, it is important that any relation between both sightings is explored. Ideas originally developed in the area of link-based similarity analysis [2, 14] are adapted herein for: (a) identifying similar individuals and objects in a space of plausible scenarios, and (b) supporting the generation of hypothetically combined scenarios to explore the implications of plausible matches.
2. *Coverage* to generate scenarios from a wide range of data sources, including factual data, collected intelligence, and hypothesised but unsubstantiated information. This requires matching specific data (e.g. the names of discovered chemicals) with broader (and possibly subjective) knowledge and

other vague information contents. Such knowledge and information may be abstractly specified in the knowledge base, e.g. "a chemical being highly explosive". Similarly, matching attributes of partially identified objects and individuals may involve comparing vague features, such as a person's apparent height, race and age. This suggests the use of a formal mathematical theory that is capable of capturing and representing ill-defined and imprecise linguistic terms, which are common in expressing and inferring from intelligence knowledge and data. Fuzzy systems methods are therefore introduced to compositional modelling to decide on the applicability of scenario fragments and their compositions.

2.2 Plausible Scenario-Based Intelligence Monitoring

Monitoring intelligence data for evidence of potential serious criminal activity, especially terrorist activity, is a non-trivial task. It is not known in advance what aspects of such activity will be observed, and how they will be interconnected. There are nevertheless, many different ways in which a particular type of activity may be arranged. Hence, conventional approaches to monitoring, which aim to identify pre-specified patterns of data, are difficult to adapt to this domain.

Although general and potentially suitable, the model-based approach adopted here may lead to systems that generate a large number of plausible scenarios for a given problem. It is therefore necessary for such a system to incorporate a means to sort the plausible scenarios, so that the generated information remains manageable within a certain time frame. For this purpose, scenario descriptions are presented to human analysts with measurements of their reliability, risk, and urgency. Each of these features may be assessed by a numeric metric. However, intelligence data and hypotheses are normally too vague to produce precise estimates that are also accurate. Therefore, a novel fuzzy mechanism is devised to provide an appropriate method of assessing and presenting these factors. The framework also covers additional tools such as a facility to propose additional information sources (by exploring additional, real or hypothesised, evidence that may be generated in a given scenario).

Figure 2 shows a specification of the general framework given in Fig. 1. Technical modules include:

- Fuzzy Feature Selection carries out semantics-preserving dimensionality reduction (over nominal and real-valued data).
- Fuzzy Learning provides a knowledge modelling mechanism to generalise data with uncertain and vague information into mode fragments.
- Fuzzy Iterative Inference offers a combination of abductive and deductive inferences, capable of reasoning with uncertain assumptions.
- Flexible CSP (constraint satisfaction problem-solver) deals with uncertain and imprecise constraint satisfaction, subject to preference and priority.
- Fuzzy Interpolative Reasoning enables approximate inference over sparse knowledge base, using linear interpolation.
- Flexible ATMS is an extended truth-maintenance system that keeps track of uncertain assumption-based deduction.

– Flexible Coreference Resolution implements a link-based identity resolution approach, working with real, order-of-magnitude, and nominal values.
– Fuzzy Aggregation performs information aggregation by combining uncertain attributes as well as their values.
– Fuzzy Evidence Evaluation performs evidence assessment, including discovery of misleading information, and generates evidence-gathering proposal.
– Fuzzy Risk Assessment computes potential loss-oriented risk evaluation through fuzzy random process modelling.

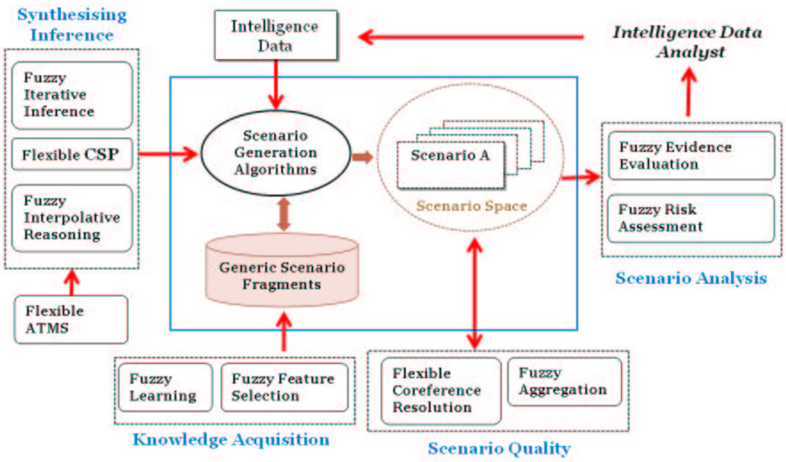

Fig. 2. Instantiated Architecture

Systems built following the approach of Fig. 2 can help to improve the likelihood of discovering potential threats posed by criminal or terrorist organisations. The reasoning of such a system is logical and readily interpretable by human analysts. Thus, it can be very helpful in supporting human analysts when working under time constraints. For instance, this may aid in avoiding premature commitment to certain seemingly more likely but unreal scenarios, minimising the risk of producing incorrect interpretations of intelligence data. This is of particular interest to support staff investigating cases with unfamiliar evidence. The resulting approach may also be adapted to build systems that facilitate training of new intelligence analysts. This is possible because the underlying inference mechanism and the knowledge base built for intelligence data monitoring can be used to artificially synthesise various scenarios (of whatever likelihood), and to systematically examine the implications of acquiring different types of evidence.

3 Illustrative Component Approaches

As a knowledge-based approach to building decision support systems, any implementation of the framework proposed above will require a knowledge base to begin with. The first part of this section will then introduce a number of recent advances in developing data-driven learning techniques that are suitable to derive such required knowledge from potentially very complex data. The second part will describe one of the key techniques that support scenario composition, especially for situations where limited domain knowledge is available. The third and final part of the section will demonstrate how risks of generated scenarios may be estimated. Figure 3 outlines a simplified version of the framework which may be implemented using the techniques described herein.

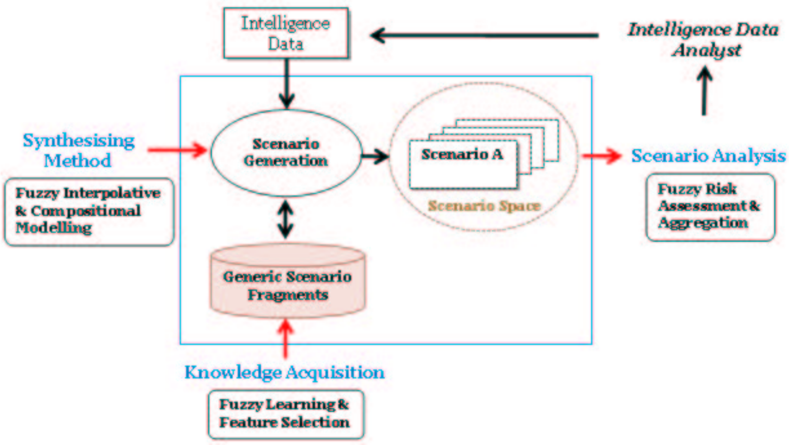

Fig. 3. Focussed Illustration

All of these approaches have been developed using fuzzy and rough methods. These techniques will be introduced at conceptual level with illustrative examples. Mathematical and computational details are omitted, but can be found in the relevant references.

3.1 Fuzzy Learning and Feature Selection

In general, an initial knowledge base of generic scenario fragments is built partly by generalising historical intelligence data through computer-based induction, and partly through manual analysis of past terrorist or criminal activity. This work focusses on the automated induction of model fragments.

Fuzzy Descriptive Learning Many real-world problems require the development and application of algorithms that automatically generate human interpretable knowledge from historical data. Such a task is clearly not just for learning model fragments.

Most of the methods for fuzzy rule induction from data have followed the so-called precise approach. Interpretability is often sacrificed, in exchange for a perceived increase in precision. In many cases, the definitions of the fuzzy sets that are intended to capture certain vague concepts are allowed to be modified such that they fit the data better. This modification comes at the cost of ruining the original meaning of the fuzzy sets and the loss of transparency of the resulting model. In other cases the algorithms themselves generate the fuzzy sets, and present them to the user. The user must then interpret these sets and the rules which employ them (e.g. a rule like: If *volume* is Tri(32.41, 38.12, 49.18), then *chance* is Tri(0.22, 0.45, 0.78), which may be learned from the data presented in Fig. 4). In some extreme cases, each rule may have its own fuzzy set definition for every condition, thereby generating many different sets in a modest rule base. The greatest disadvantage of the precise approach is that the resulting sets and rules are difficult to match with human interpretation of the relevant concepts.

As an alternative, there exist proposals that follow the descriptive (or linguistic) approach. In such work no changes are made to human defined fuzzy sets. The rules must use the (fuzzy) words provided by the user without modifying them in any way. One of the main difficulties with this approach is that the possible rules available are predetermined, equivalently speaking. This is because the fuzzy sets can not be modified, and only a small number of them are typically available. Although there can be many of these rules they are not very flexible and in many cases they may not necessarily fit the data well (e.g. a rule like: If *volume* is Moderate, then *chance* is High, which may be learned from the data and predefined fuzzy sets given in Fig. 5). In order to address this problem, or at least partially, linguistic hedges (aka. fuzzy quantifiers) are employed.

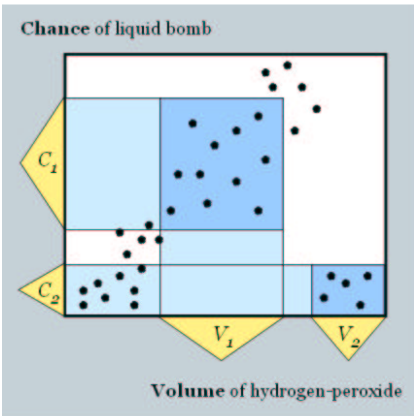

Fig. 4. Precise Modelling

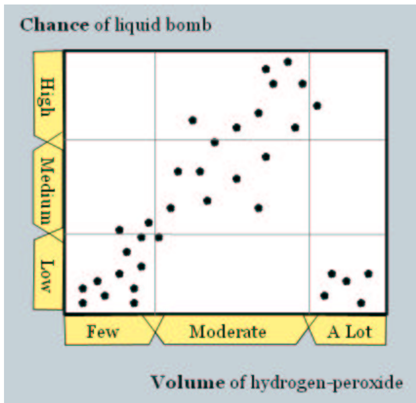

Fig. 5. Descriptive Modelling

The concept of linguistic hedges has been proposed quite early on in fuzzy systems research [33]. Application of such a hedge to a fuzzy set produces a new fuzzy set, in a fixed and interpretable manner. The interpretation of the resultant set emanates from the original fuzzy set and a specific transformation that the hedge implies. In so doing, the original fuzzy sets are not changed, but the hedged fuzzy sets provide modifiable means of modelling a given problem and therefore, more freedom in representing information in the domain.

This research adopts the seminal work of [18] which champions this approach. Figure 6 illustrates the ideas: Descriptive fuzzy system models are produced with a two-step mechanism. The first is to use a precise method to create accurate rules and the second to convert the resulting precise rules to descriptive ones. The conversion is, in general, one-to-many. It is implemented by using a heuristic algorithm that derives potentially useful translations and then, by employing evolutionary computation to perform a fine tuning of these translations. Both steps are computationally efficient. The resultant descriptive model is ready to be directly applied for inference; no precise rules are needed in runtime.

Note that Fig. 6 shows the learning of a “model” in a general sense. Such a model may be a set of conventional production fuzzy if-then rules, or one or more generic model fragments which involve not only standard conditions but also assumptions or hypotheses that must be made in order to draw conclusions.

Fuzzy-Rough Feature Selection Feature selection [9, 15] addresses the problem of selecting those characteristic descriptors of a domain that are most informative. Figure 7 shows the basic procedures involved in such a process. Unlike other dimensionality-reduction methods, feature selectors preserve the original meaning of the features after reduction.

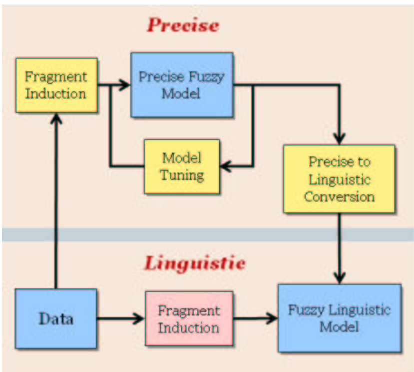

Fig. 6. Two-Step Learning of Descriptive Models

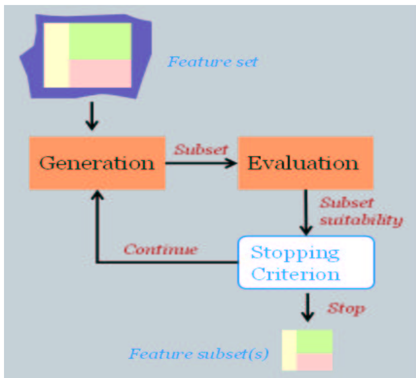

Fig. 7. Feature Selection Process

There are often many features involved in intelligence data, and combinatorially large numbers of feature combinations, to select from. It might be expected that the inclusion of an increasing number of features would increase the likelihood of including enough information to distinguish between classes. Unfortunately, this is not necessarily true if the size of the training dataset does not also increase rapidly with each additional feature included. A high-dimensional dataset increases the chances that a learning algorithm will find spurious patterns that are not valid in general. Besides, more features may introduce more measurement noise and, hence, reduce model accuracy [7].

Recently, there have been significant advances in developing methodologies that are capable of minimising feature subsets in an imprecise and uncertain environment. In particular, a resounding amount of research currently being done utilises fuzzy and rough sets (e.g. [11, 16, 17, 27, 30, 32]). Amongst them is the fuzzy-rough feature selection algorithm [8, 10] that works effectively with discrete or real-valued noisy data (or a mixture of both), without the need for user-supplied information. This approach is suitable for the nature of intelligence data and hence, is adopted in the present work. A particular implementation is done via hill-climbing search, as shown in Fig. 8. It employs the fuzzy-rough dependency function, which is derived from the notion of fuzzy lower approximation, to choose those attributes that add to the current candidate feature subset in a best-first fashion. The algorithm terminates when the addition of any remaining attribute does not result in an increase in the dependency. Note that as the fuzzy-rough dependency measure is nonmonotonic, it is possible that the hill-climbing search terminates having reached only a local optimum.

3.2 Fuzzy Interpolative Reasoning

In conventional approaches to compositional modelling, the completeness of a scenario space depends upon two factors: (a) the knowledge base must cover all essential scenario fragments relevant to the data, and (b) the inference mechanism must be able to synthesise and store all combinations of instances of such fragments that constitute a consistent scenario. However, in practice, it is difficult, if not impossible, to obtain a complete library of model fragments. Figure 9 shows an example, where a sparse model library consisting of two simplified model fragments (i.e. two simple if-then rules) is given:

$Rule_i$: If *frequency* is None then *attack* is Unlikely

$Rule_j$: If *frequency* is Often then *attack* is Likely

In this case, with an observation that states "*frequency* is Few", no answer can be found to the question "Will there be an attack"? A popular tool to deal with this type of problem is fuzzy interpretative reasoning [1, 31]. In this work, the transformation-based approach as proposed in [5, 6] is employed to support model composition, when given an initial sparse knowledge base.

The need for a fuzzy approach to interpolation is obvious: The precision degree of the available intelligence data is often variable. The potential sources of such variability include vaguely defined concepts (e.g. materials that constitute a "high explosive", certain organisations that are deemed "extremist"), quantities (e.g. a "substantial" amount of explosives, "many" people) and specifications of importance and certainty (e.g. in order to deploy a radiological dispersal device, the perpetrator "must" have access to radioactive material and "should" have an ideological or financial incentive). Finding a match between the given data and the (already sparse) knowledge base cannot in general be achieved precisely.

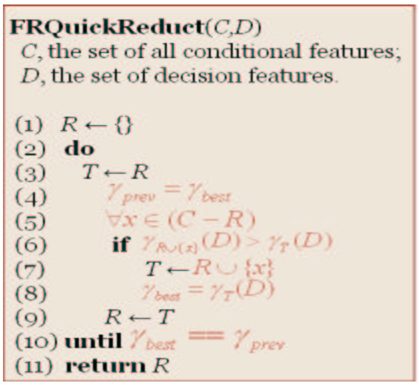

Fig. 8. Fuzzy-Rough Feature Selection

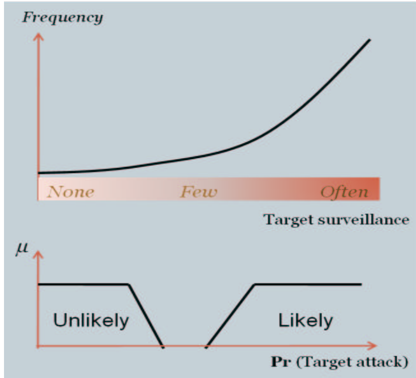

Fig. 9. Spare Knowledge Base

Figure 10 illustrates the basic ideas of fuzzy interpolative reasoning. It works through a two-step process: (a) computationally constructing a new inference rule (or model fragment in the present context) via manipulating two given adjacent rules (or related fragments), and (b) using scale and move transformations to convert the intermediate inference results into the final derived conclusions.

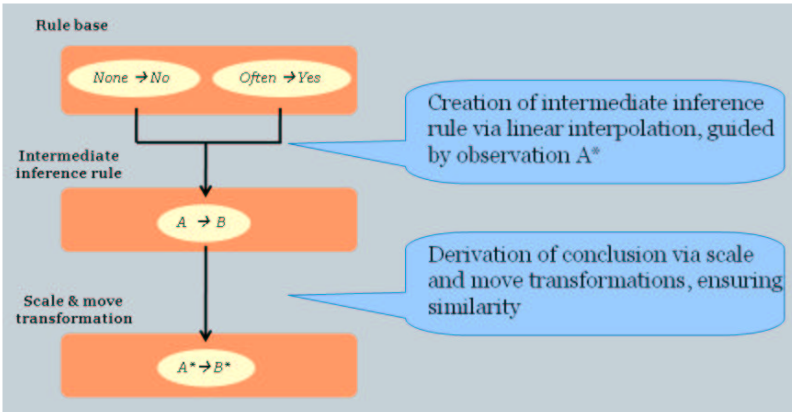

Fig. 10. Transformation-Based Fuzzy Interpolation

3.3 Fuzzy Risk Assessment

In developing intelligent systems for intelligence data monitoring, a trade-off needs to be considered. On the one hand, it is important not to miss out any potentially significant scenarios that may explain the observed evidence. On the other hand, too many unsorted and especially, spurious scenarios may confuse human analysts. Thus, it is desirable to be able to filter the created scenario space with respect to certain objective measures of the quality of the generated scenario descriptions. Fortunately, as indicated previously, preferences over different hypothetical scenarios can be determined on the basis of the reliability, risk and urgency of each scenario.

The *reliability* of a generated scenario may be affected by several distinct factors: the given intelligence data (e.g. the reliability of an informant), the inferences made to abduce plausible scenarios (e.g. the probability that a given money transfer is part of an illegitimate transaction), and the default assumptions adopted (e.g. the likelihood that a person seen on CCTV footage is identified positively). The *urgency* of a scenario is inversely proportional to the expected time to completion of a particular terrorist/criminal activity. Therefore, an assessment of urgency requires a (partial) scenario to be described using the scenario's possible consequences and information on additional actions required to achieve completion. The *risk* posed by a particular scenario is determined by its potential consequences (e.g. damage to people and property). Whilst these are very different aspects that may be used to differentiate and prioritise composed scenarios, the underlying approaches to assess them are very similar. In this paper, only the scenario risk aspect is discussed.

Risk assessment helps to efficiently devise and deploy counter measures, including further evidence gathering of any threat posed by the scenario concerned. However, estimating the risk of a plausible event requires consideration of variables exhibiting both randomness and fuzziness, due to the inherent nature of intelligence data (and knowledge also). Having identified this, in the present work, risk is estimated as the mean chance of a fuzzy random event [4, 29] over a pre-defined confidence level, for each individual type of loss. In particular, plausible occurrence of an event is considered random, while the potential loss due to such an event is expressed as a fuzzy random variable (as it is typically judged linguistically). In implementation, loss caused by an event is modelled by a function mapping from a boolean sample space of {Success, Failure} onto a set of nonnegative fuzzy values. Here, success or failure is judged from the criminal's viewpoint, in terms of whether they have carried out a certain activity or not.

Risks estimated over different types of loss (e.g. range of geometric destruction and number of casualties) can be aggregated. Also, assessments obtained using different criteria (e.g. resource and urgency) may be integrated to form an overall situation risk. Such measures may be utilised as flexible constraints [19] imposed over an automated planning process, say for police resource deployment. This can help to minimise the cost of successful surveillance, for example. To generalise this approach further, order-of-magnitude representation [22, 25] may be introduced to describe various cost estimations. Figure 11 shows such an application.

4 Conclusion

This paper has introduced a novel framework upon which to develop intelligent decision support systems, with a focussed application to intelligence data monitoring and interpretation. It has outlined methods that can aid intelligence analysts in considering as widely as possible a range of emerging scenarios which are logically inferred and justified, and which may each reflect organised criminal/terrorist activity. This work has indicated that some of the recent advances in fuzzy and rough techniques are very successful for data-driven systems modelling and analysis in general, and for performing the following tasks in particular:

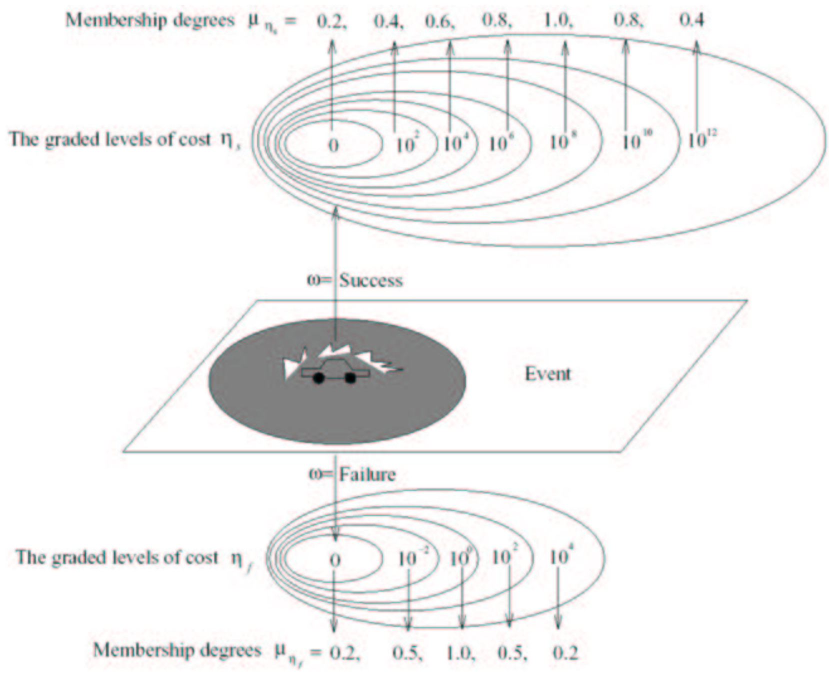

Fig. 11. Risk Assessment

- Fragment induction
- Feature selection
- Interpolative reasoning
- Model composition
- Constraint satisfaction
- Truth maintenance
- Co-reference resolution
- Information aggregation
- Evidence evaluation
- Risk assessment

However, important research remains. The following lists a number of further issues that are worthy of investigation and/or development:

- Learning hierarchical model fragments
- Hierarchical and ensemble feature selection
- Unification of scenario generation algorithms
- Dynamic co-reference resolution and information fusion

– Evidence-driven risk-guided scenario generation
– Reconstruction of reasoning process
– Discovery of rare cases
– Meta-feature learning and selection for scenario synthesis

Further studies will help to consolidate and broaden the scope of applications of fuzzy set and rough set theories. In particular, the proposed framework and associated techniques can be adapted to perform different tasks in intelligence data modelling and analysis, such as: investigator training, policy formulation, and multi-modal profiling. Additionally, this work may be applied to accomplishing tasks in other domains, such as academic performance evaluation and financial situation forecasting. Finally, it is worth noting that most of the component techniques within the current framework utilise fuzzy set theory as the mathematical foundation. It would be very interesting to investigate if alternative approaches may be developed using rough sets or their extensions in an analogous manner. Also, the employment of directly combined and/or hybrid fuzzy-rough systems may offer even more advantages in copying with complex decision support problems. The research on fuzzy-rough feature selection as adopted within this framework has demonstrated, from one aspect, such potential.

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