A Model based on Rough Sets for Situation Comprehension and Projection

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***Abstract*—We present our results on the definition of a formal and interactive situation model improving comprehension of situations and supporting reasoning on projections of situations. The model is based on the rough sets and allows the creation of lattices that fuse the elements of an environment according to different perspectives and requirements of interest for a human operator. To support rapid decision making on dissimilarities between recognized and projected situations, we adopt some measures defined on the lattices. In many scenarios, like in emergency response, this can support the generation of early warnings that may help the human operators in identifying future dangerous events. An early evaluation has been accomplished by considering an illustrative case study based on real scenarios for management of vessel traffic.**

***Index Terms*—Situation Modelling; Rough Sets; Decision Support Systems; Lattice-based Knowledge Representation**

I. Introduction and Motivation

In complex and dynamic environments, having good situation awareness (SA) is essential to make rapid and coherent decisions. Roughly speaking, SA means to be aware of what is happening in the environment, by understanding the meaning of the perceived information, interpreted by using the correct mental models. From a computational viewpoint, situations are representations of individual pieces of raw information (like sensor data) at a higher level of abstraction, in terms of domain-relevant concepts. Regrettably, achieving good SA is not a trivial task. In [1], Endsley analyzed the main reasons of human difficulties in achieving and maintaining proper levels of SA. Part of the main results of her work was a taxonomy of the common issues that hinder a good SA. Most of the errors are related with the difficulty in perceiving data and assigning a correct meaning to it. This happens especially due to poor mental models that do not allow human operators to understand part of the information. In our opinion, such a critical issue can be softened by means of: i) proper computational and explicit models of situations, which can be directly seen and manipulated by the human operators; ii) techniques and approaches that allow the human operators to analyze the situations, to reason about them, project them into the future and track their evolution over the time. Such approaches should be concretely implemented in human computer interaction techniques and in decision support systems able to sustain the process of SA formation and the rapid decision making. Many models and computational approaches for situation representation, identification and projection have been proposed so far [2]. Specifically, situation identification techniques are usually divided into two categories [3]: learning-based and specification-based techniques. The former, which comprises techniques like Naive Bayes, hidden Markov model, neural networks, have the capability to identify situations even in an unsupervised way, but usually they do not provide a formal and explicit model of the situations. This may represent an issue in sustaining a deep understanding of the perceived information by the human operators, as it is not possible for them to "see" the situation and to interact with it. The second category consists of ontological approaches, fuzzy cognitive maps [4], evidence theory and other logic-based techniques. Such models have the powerful capability of formally and explicitly representing the situation, but usually they are not so flexible as to adapt to the users' interactions or to adapt to heterogeneous domains without substantial modifications.

In this work, we present a computational model of situations that is formal, explicit and actionable (in the sense that it helps in making rapid decisions) based on rough sets theory. The situation is represented by means of: i) an *information table* that contains the main elements of the environment (i.e., objects) and their attributes and ii) a *lattice* that graphically represents such a table according to different, user-defined, information fusion criteria. It supports the comprehension of the current situation as it provides the human operators with detailed insights on the current state of the environment by means of the information table and with an interactive approach for reasoning on the situations thanks to the lattice that evolves over the time. Such a lattice supports the reasoning on group of similar or undistinguishable objects (thus reducing the number of elements the human operators need to observe) and it supports also the reasoning on future evolutions and projections of situations. In such sense, it can accelerate the decision making processes. Moreover, the model is flexible as it is possible to change the information fusion criteria for generating a different lattice (that provides a different viewpoint on the data) even at run-time. It is also a formal model, as it is based on rough set theory, thus enabling the possibility to compute measures of similarity among lattice structures. Such measures are useful for quantifying the differences among situations at different time intervals. It can be exploited in the definition of interactive systems for SA, as human operators can change at runtime the set of attributes on which they want to focus on or they can change the information fusion criteria. Lastly, the proposed model is domain-agnostic.

II. Theoretical Background

A. Situation Awareness

A widely accepted definition of situation awareness is that proposed by Endsley [5], which considers three levels of SA: level 1 (*Perception*) refers to the perception of elements in the environment; level 2 (*Comprehension*) is the comprehension of the meaning of such elements in relation to goals and objectives; level 3 (*Projection*) regards the projection of their status in the near future. Such three levels should not be intended as sequential and linear, but they are iterative, as comprehension drives the search for new data, and the perception of new data feeds the comprehension process. Systems and applications leveraging on such model, for supporting users in gaining and maintaining high level of SA in decision making processes, need to be proper designed. A fundamental component of situation awareness design process is the phase of analysis of goals and requirements. This can be realized by following the Goal-Directed Task Analysis (GDTA) [6] methodology, which is a cognitive task analysis focusing on the goals that human operators must achieve and the information requirements they need to make informed decisions. The result of GDTA is a hierarchical structure establishing the requirements of the system and representing the users' goals. Such an approach will be exploited in our work in order to define the initial information table on which the lattices can be constructed following some information fusion criteria.

B. Rough Sets

In this work we base our approach on the rough sets originally proposed in [7] and further investigated by several scholars. In particular, we leverage on the results of Yao, e.g. [8] [9], for the creation of lattices of partitions that are at the core of our situation model. Rough sets are usually adopted to formally approximate a set with a pair of sets which give the lower and the upper approximation of the original set. At the core of this formalism, there are the concepts of information system and indiscernibility (or indistinguishability) relation. More formally, let us consider $I = (U, A)$ an information system, where U is a set of objects and A is a set of attributes such that $a : U \to V_a$ for every $a \in A$, where V_a is the set of values that a can take. An information table IT assigns a value $a(x)$ from V_a to each attribute a and object x in the universe U. Given any subset of attributes, $E \subseteq A$, we can define an equivalence relation as:

$$IND(E) = \{(x, y) \in U \times U | \forall a \in E, a(x) = a(y)\} \quad (1)$$

$IND(E)$ states that x and y are indiscernible (or indistinguishable) by attributes from E. An equivalence relation can be defined based on a set of attributes in an information table so that two objects are equivalent if and only if they have the same value on every attribute. Given an equivalence relation E, we can define an equivalence class:

$$[x]_E = \{y | y \in U,\ x\ E\ y\} \quad (2)$$

Suppose $H \subseteq U$ is a set of objects we want to describe, or approximate, with the equivalence classes. With rough sets we can approximate H by constructing its lower and upper approximations:

$$\underline{apr(H)} = \{x | x \in U,\ [x]_E \subseteq H\} \quad (3)$$

$$\overline{apr(H)} = \{x | x \in U,\ [x]_E \cap H \neq 0\} \quad (4)$$

III. A computational approach for situation modelling and reasoning

We report in this section the approach proposed for reasoning on situation and gathering early warning signals on situation projections. The idea is to model a situation as a lattice of partitions, where a partition represents a set of objects/elements that are fused according to GDTA level 2 requirements. Starting from a situation modelled with a lattice, a set of projections may be derived by changing some attributes of the objects/elements. The formalism behind the approach is based on rough sets described in section II and the overall approach is depicted in Fig. 1. The starting point is a GDTA [6] providing requirements for the three levels of SA. From SA level 1 requirements, we can define an information table reporting on the rows the objects/elements to be perceived at level 1, $O_1, ..., O_n$, and on the columns the attributes, $a_1, ..., a_m$. We can also add an additional column with a decisional attribute to classify the level 1 objects but this is not reported in the figure. From this information table, we can group objects that satisfy particular criteria by defining appropriate functions. For instance, let be U the universe of all the objects to be perceived and let define a distance function $D : U \times U \to R^+$. For each $d \in R^+$ we can define, using the formalism proposed in [8], a neighbourhood of x:

$$n_d(x) = \{y | D(x, y) \leq d\} \quad (5)$$

where d is a threshold, x and y are level 1 objects. In this case, the subset of attributes related to position is used to create a group of objects. Another example may concern grouping objects that are indistinguishable with regards to one or more attributes. For this purpose, we can use directly a relation such as Eq. (1). In this case, for instance, if a subset B is the subset of attributes related to the velocity of an object, we can fuse objects that are equivalent with respect to speed. In this way, taking into account the constrain that SA level 2 requirements pose on the criteria to fuse information, we can

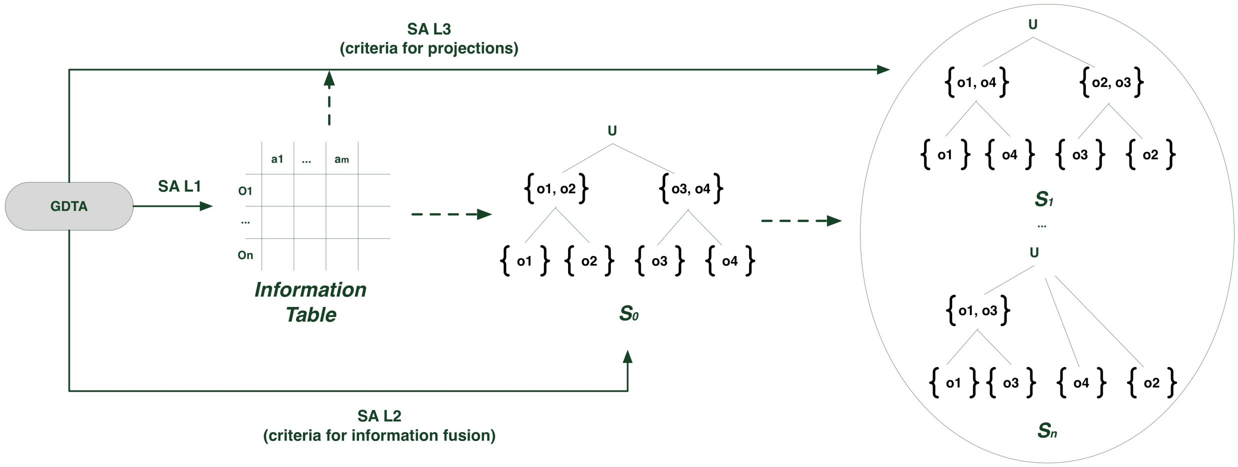

Fig. 1. Overall approach

define a lattice of partitions where each partition represents a group of objects that are equivalent with respect to a subset of attributes. For instance, S_0 represents a situation where objects $\{O_1, O_2\}$ and $\{O_3, O_4\}$ are equivalent with respect to B. This structure may be refined by considering different nested subsets of attributes. In fact, if we consider $C \subset B$ we may discern the four objects in S_0. It is worth mentioning that using incremental learning approaches, such as the one described in [10], the information table may be incrementally updated when attributes values vary over time, and this implies updating the corresponding lattices structures. If we consider all the subsets of attributes that can be also nested, e.g. $... \subset C \subset B \subset A$, it is possible to derive a set of lattices such as $S_1, ..., S_n$, and some of them can be possible evolutions of the recognized situation S_0. A human operator may have a good mental model and expertise to foresee possible evolutions starting from a recognized situation, such as S_0, but he/she may rather have some difficulties in reasoning on conceptual and informative differences among the possible evolutions and/or between a recognized situation and its evolution. The following subsections provide details on situation modelling with the rough sets formalism and on heuristics to support rapid reasoning on situation projections.

A. *Situation Model based on Rough Sets*

A situation modelled with the rough set theory is a combination of an *information table* IT and a lattice of partitions L_B over a subset of attributes B. Formally, we define $S =< IT, L_B >$ where IT is an *information table* and $B \subseteq A$ is a subset of attributes used to partition the elements of the environment. The lattice groups objects with respect to a specific criterion, usually embedded in SA level 2 requirements. Thus, for instance, if we use the formalism of Eq. (5) the lattice groups neighbour objects. If we use Eq. (2), the objects are equivalence classes. From the perspective of a human operator, the tuple $< IT, L_B >$ is more informative with respect to other situation models. In fact, besides having information on the attributes of all the objects of an environment, the human operator has a human-readable structure that gives information on groups of objects that are equivalent with respect to the criteria of his/her interest. As mentioned, if B is the subset of attributes related to trajectory or speed or other criteria, lattice L_B gives rapid information on the objects that are indistinguishable with respect to these attributes. The human operator can set the criteria of his/her preferences, giving rise to different subsets of attributes and look at the equivalent objects.

Another interesting aspect of modelling situations with rough sets is the concept approximation, i.e. the possibility of approximating an unknown concept with a known concept, with the support of three regions. Let be $[x]_E$ a group of objects indistinguishable with respect to the subset E. Let us reason on the objects of an environment, and suppose we include in IT a decisional attribute a_d that allows to classify these objects with respect to a class (e.g. "safe"). So, in this case, the situation model is $S =< IT \cup A_d, L_E >$, where A_d is the set of decisional attributes. Suppose $H \subseteq U$ is a subset of objects we want to describe, or approximate, with the equivalence classes. With rough sets we can approximate H by constructing its lower and upper approximations as described by Eq. (3) and Eq. (4) that can be also interpreted in terms of regions:

$$POS(H) = \underline{apr}(H) \tag{6}$$

$$NEG(H) = U - \overline{apr}(H) = \{x | x \in U, \ [x]_E \cap H = 0\} \tag{7}$$

$$BND(H) = \overline{apr}(H) - \underline{apr}(H) = \{x | x \in U, \ [x]_E \cap H \neq 0 \, , [x]_E \nsubseteq H\} \tag{8}$$

Eq. (6) is the positive region and includes all the equivalence classes hat can be positively classified as belonging H, Eq. (7) is the negative region and includes objects that can be definitely ruled out as members of H and Eq. (8) is the

Fig. 2. Classification based on probabilistic rough sets

boundary region consisting of objects that can neither be ruled in nor ruled out as members of the target set H.

This can be done also introducing a degree of tolerance as reported in [11]. We can introduce three-way decision rules, namely, positive rules for accepting an object to be a member of H, negative rules for rejecting, and boundary rules for deferring a definite decision. Let $P(H|[x]_E)$ be the conditional probability of an object belonging to H given that the object belongs to $[x]_E$. This probability can be estimated as

$$P(H|[x]_E) = \frac{|H \cap [x]_E|}{|[x]_E|} \tag{9}$$

where $|.|$ is the cardinality operator. If we consider probabilistic rough sets [11], a pair of thresholds α and β with $\alpha > \beta$ can be introduced, and by using the conditional probability defined in Eq. (9), the three regions in Eq. (6), Eq. (7) and Eq. (8) can be formulated as follows:

$$POS(H) = \{x | x \in U,\ P(H|[x]_E) \geq \alpha\} \tag{10}$$

$$NEG(H) = \{x | x \in U,\ P(H|[x]_E) \leq \beta\} \tag{11}$$

$$BND(H) = \{x | x \in U,\ \beta < P(H|[x]_E) < \alpha\} \tag{12}$$

Fig. 2 shows the regions we can define on the basis of probabilistic rough set model. The value of these three regions for a human operator is easy to explain. Suppose H is the subset of objects that for a specific situation are classified as "safe" or "good". When a class of equivalence, i.e., a group of objects indistinguishable with respect to some criteria, is recognized in the current situation, with the support of Eq. (10), a human operator may know if this class can be approximated with the set of "good" or "safe" objects. This can improve the comprehension of the human operator.

B. Evaluation of Situation Projections

In this section we present two measures that can help a human operator on reasoning on situations and their evolutions. Let us define the lattice more formally. Let be $F(x)$ a non empty family of partitions (e.g. of equivalence classes or neighbourhoods), defined over a sequence of nested attributes, e.g. $A_3 \supset A_2 \supset A_1$. We define the equivalence relations on this sequence of subsets $I = E_{A_3} \subset E_{A_2} \subset E_{A_1} \subset E_0 = U \times U$. The union of these families for all the elements of an universe defines a lattice of partitions:

$$L = \cup_{i=1}^{|U|} F(x_i) \tag{13}$$

We can define a dissimilarity measure [12] between two lattices as

$$Dis(L_1, L_2) = \frac{1}{|U|} \sum_{i=1}^{|U|} \frac{|L_1(x_i) \triangle L_2(x_i)|}{|U|} \tag{14}$$

where $|L_1(x_i) \triangle L_2(x_i)|$ is the cardinality of a symmetric difference between the family of partitions: $|F_1(x_i) \cup F_2(x_i)| - |F_1(x_i) \cap F_2(x_i)|$. The symmetric difference removes the common elements between two partitions, and can be considered as a sort of dissimilarity between the two structures. We can define the similarity as:

$$Sim(L_1, L_2) = 1 - D(L_1, L_2) \tag{15}$$

Eq. (14) and Eq. (15) can be used for early evaluation of the projections of a situation. Starting from the situation at time t_0, defined by the tuple $S_0 =< IT, L_B >$ over a subset B of attributes, a human operator with a good mental model for projection can foresee the evolution on some parameters of one or more objects, and update the information table. This will create new situations $S_1, ..., S_n$ that are possible projections of S_0. These projections may be evaluated with respect to S_0 by using Eq. (14) and Eq. (15) to understand if they differ or not. The human operator can also decide to change the subset of attributes for the creation of lattice structures representing projections, and this can be useful if the criteria behind SA level 3 requirements differ from the ones of SA level 2. Also in this case, Eq. (14) and Eq. (15) can give rapid information on differences with respect to the *status quo*. Lastly, the partitions of the projected situations may be classified according to the three-way decision rules, to approximate the new classes of the projected situations with the known ones. This can help in improving the comprehension of the projected situations.

C. Added value of the approach

The proposed approach is based on a situation model that is formally described, interactive and human-understandable. Furthermore, it offers to human operators a high degree of flexibility that consists in the possibility of showing different perspectives of a situation by allowing the selection (in an interactive way) of different subsets to be used for creation of partitions. We consider the following added values for a human operator in modelling situations as described:

- improving perception and comprehension, via the provision of explicit information on the status of each element to be perceived and of a human readable structure such as the lattice of partitions
- supporting the reasoning on different possibilities of forming partitions, by allowing him/her to identify different subsets of attributes that may match different SA level 2 criteria to fuse objects
- improving comprehension of the situations with concept approximation and classification, allowing a human operator to approximate the partitions of a lattice structure with known concepts

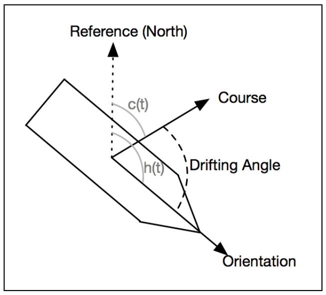

Fig. 3. Drifting angle [15]

- supporting rapid decision making with measures of dissimilarity between recognized and projected situations.

It is worth noting that the adoption of a formal setting based on rough sets has also additional benefits in SA applications that we need to further investigate. In literature there are several example of rule induction from incomplete datasets, such as [13], and classification under incomplete information [14] that can be very useful in concrete operational scenarios where sensor data may be lost or where the information is incomplete. Moreover, there exist several approaches for attribute reduction in rough sets and the concept of *reduct*, i.e., the subset of attributes which can fully characterize the knowledge in the information table, can be useful to model situations for which the dynamic of the elements/objects of the environment can be precisely characterized by a subset of attributes. This aspect has both computational and cognitive benefits since it allows a reduction of the information table and allows human operators to focus attention on the correct aspects of the information.

IV. Case Study: Vessel Traffic

A. Scenario

In the maritime domain, it is crucial to understand why certain vessels movements take place. Normal and secure conditions are related with the movement of a ferry that always sails between two harbors. If the ferry moves on a different route, a possible threat may have happened. For instance, the engine may have broken or the ferry may be hijacked. A surveillance operator, by observing the routes of the vessel between the two harbors, can identify such dangerous situations and proceed to further investigations. In such situations, the human operator intervenes because he/she knows (i.e., he/she has the right mental model) the normal behavior of vessels in the observed environment, and so he/she can identify abnormal conditions [15]. But, in case of many vessels, different kind of ships and heavy traffic, a human operator may be not able to early identify dangerous and abnormal situations. In the following example, we consider a scenario of drifting vessels in order to demonstrate how the proposed model of situations can be helpful in supporting human operators to anticipate abnormal conditions and to be early warned of possible dangerous situations. A vessel may start to drift due to engine failure, that makes the vessel uncontrollable. A vessel is said to be drifting [15] when it is moving slowly, usually with a velocity $v(t)$ between 3 and 5 knots, and its course $c(t)$ and orientation $h(t)$ have a significant difference, usually more than 30°, as depicted in Fig. 3. We want to identify potential drifting vessels for supporting the human operator in understanding the movements of such vessels, so to early act for keeping safe the overall situation in the stretch of water under control. Let us consider the information table in Table I that reports the values of a group of 5 vessels in an area under maritime surveillance by the human operator. The position and the drifting angles of the vessels are depicted in Fig. 4. In particular, we assume that the set of attributes A of the information table is $A = \{Velocity, DriftingAngle, DistancefromCoast, Type\}$, whose elements may assume the following values:

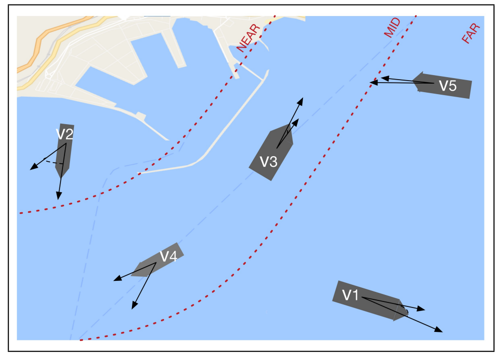

Fig. 4. Position and drifting angles of the five vessels in the case study.

TABLE I
Information table for the vessel traffic scenario

	Velocity	Drifting Angle	Distance from coast	Type	Decision
V1	LOW	LOW	FAR	Cargo	S
V2	LOW	MID	NEAR	Ferry	D
V3	MID	LOW	MID	Cargo	S
V4	MID	MID	MID	Research	S
V5	MID	LOW	FAR	Research	S

- Velocity: 1) LOW ($0\ knots < v(t) \le 5\ knots$); 2) MID ($5\ knots < v(t) \le 15 knots$); 3) HIGH ($v(t) > 15 knots$)
- Drifting Angle $[c(t) - h(t)]$: 1) LOW ($\le 15°$); 2) MID ($> 15°$ and $\le 30°$); 3) HIGH ($> 30°$)
- Distance from the coast: 1) NEAR ($\le 2 miles$); 2) MID ($> 2 miles$ and $\le 10 miles$; 3) FAR ($> 10 miles$)
- Type: 1) Cargo (commercial vessel); 2) Ferry (a ferry that usually moves between two points); 3) Research (vessel designed to perform research at sea).

The column *Decision* represents the decisional attribute that will be used in section IV-C for classifying the set of vessels: D stands for dangerous while S for safe.

B. Supporting Situation Comprehension

Let us suppose that, at time $t = t_0$, the human operator selects, as the criterion for information fusion, the attribute *Drifting Angle*, by using the equivalence relation of Eq. (2). As a result, we have a subset $B = \{DriftingAngle\} \subset A$, which leads to the following equivalence subclasses of vessels: {V1, V3, V5} and {V2,V4}. With this partition, we obtain the lattice showed in Fig. 5.A. Even with this simple lattice that has been constructed just with one attribute out of 4 four, the human operator knows which group of vessels needs attention: {v2,v4}, because the drifting angle of such vessels may be an hint of a drifting situation. The human operator can further verify if such situation holds by considering another attribute, which could be the *velocity* of the vessels. Formally, we consider the sequence of nested attributes $C = \{Drifting\ Angle, Velocity\} \supset B = \{Drifting\ Angle\}$. In this way, the lattice of Fig. 5.A evolves in the lattice of Fig. 5.B, which represents the situation at time $t = t_0$ with further details. The lower level of the lattice shows that the vessel $V2$ can be a potential drifter as its velocity is LOW and the drifting angle is MID. The other vessel V4 has a higher velocity, and so, with the available information, it can not be considered a drifter as its engine works well. Thus, it is possible that the vessel V4 is doing a normal and safe maneuver. Obviously, the human operator can use other information, as this becomes available, in order to further improve the comprehension of what is happening in the monitored environment, by analyzing it with evolving lattices. The human operator, by leveraging on his/her mental model and experience, on the basis of the information represented via the lattice and the information table, decides if the identified situation can be considered as still safe or it requires some actions to avoid accidents.

C. Classification of the objects with conditional probability to improve comprehension

The support to the comprehension of the human operator can be enhanced by using a decisional attribute for classifying the state of each vessel (i.e., the movement of the vessel is safe or dangerous). Indeed, it is possible to calculate the probability of each group of objects (in the lattice) belonging to the class of safe objects. In this way, the human operator can exclude a set of objects from further investigations as they are classified as being safe, and he/she can concentrate his/her effort on a (possible) smaller set of vessels. The decisional attribute (shown in the last column of Table I) can be obtained by employing some domain rules, which can be defined by the experts during the GDTA process. In this table $S = Safe$ indicates that the current movement of the vessel can be considered as normal and safe, and $D = Dangerous$ indicates the opposite situation. Using such attribute and Eq. (10), Eq. (11) and Eq. (12), it is possible to enhance the lattice of Fig. 5.A with an indication of the dangerousness of each group of vessels. Let us consider the class S of safe vessels. According to the information table I, $S = \{V1, V3, V4, V5\}$. Then, considering again the equivalence relation with respect to the set $B = \{DriftingAngle\} \subset A$, resulting in the lattice of Fig. 5.A. At the lower level of the lattice, we had two subsets {V1,V3,V5} and {V2,V4}. We want to classify these two subsets in the three regions of decision $POS(S)$ (containing groups of safe vessels), $NEG(S)$ (containing groups of not safe vessels), and $BND(S)$ that contains the group of vessels that can not be classified with the available information. By evaluating the conditional probability $P(S|[h]_B)$ of a vessel belonging to the class of $Safe$ objects S, we obtain: $P(S|\{V1, V3, V5\}) = 1$ and $P(S|\{V2, V4\}) = 0.5$. Now, suppose that $\alpha = 0.63$ and $\beta = 0.25$ (such values are defined by Yao in [11]), we can classify the two subsets in this way: $POS(S) = \{V1, V3, V5\}$, $BND(S) = \{V2, V4\}$ and $NEG(S) = \{\}$. This means that the group of vessels $\{V1, V3, V5\}$ is safe, while we defer the decision about the classification of the set $\{V2, V4\}$ when considering only the attribute $Drifting\ Angle$. By considering also the information on the velocity of the vessels (lattice of Fig. 5.B) we have: $P(S|\{V1\}) = 1$ and $P(S|\{V3, V5\}) = 1$, $P(S|\{V2\}) = 0$, $P(S|\{V4\}) = 1$, and consequently: $POS(S) = \{\{V1\}, \{V3, V5\}, \{V4\}\}$, $BND(S) = \{\}$ and $NEG(S) = \{V2\}$. In this case, the human operator is aware that the vessel V2 needs particular attention as it is classified as a potential drifter, while he/she can leave out the other vessels from further investigations.

D. Supporting Situation Projections

In order to understand the possible evolutions of the situations, the human operator performs a what-if analysis by considering a different value for one or more attributes. In particular, starting from the lattice L_0 of Fig. 5.B, the human operator supposes that the angle of vessel V2 will increase in the near future. By applying the same sequences of nested attributes $\{Drifting\ Angle\} \subset \{Drifting\ Angle, Velocity\}$, and the new value for the *Drifting Angle* of V2, the lattice L_0 will evolve in the lattice L_1 of Fig. 5.C (the differences between the two lattices are circled in red). By comparing the two lattices, the human operator observes that a new concept appears in the second lattice at the intermediate level of the hierarchy of granulation. Indeed, the subset $\{V2, V4\}$ is split in $\{V2\}$ and $\{V4\}$ due to the new value for the drifting angle. By using the dissimilarity function of Eq. (14), it is possible to quantify the differences between the two lattices and the related situations: $Dis(L_0, L_1) = 0.2$. The human operator evaluates the new situation and he/she can easily understand that the vessel $V2$ can become a drifter as the drifting angle will be higher. Considering that the new projected situation differs from the previous one, he/she can perform some actions in order to maintain the same situation as the one at time $t = t_0$. The human operator can simulate also other scenarios. For instance, he/she can suppose that vessel V2 will not increase its angle, but it increases its velocity. Another lattice will be obtained, as depicted in Fig. 5.D. The intermediate level of the hierarchy is not modified, while the two subsets $\{V2\}$ and

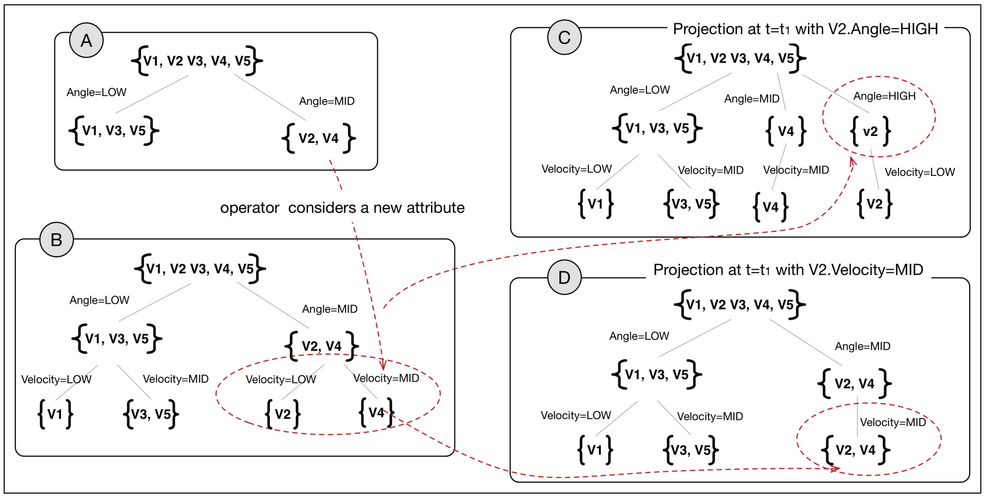

Fig. 5. Evolving lattices according to the analysis made by the human operator in the case study. A) Initial lattice with set B={Angle} at time t_0; B) Lattice with sequence of subsets of attribute B={Angle} $\subset$ C={Angle, Velocity} at time t_0; C) Lattice of one possible situation projection at time t_1 with V2.Angle=HIGH; D) Lattice of another possible situation projection at time t_1 with V2.Velocity=MID.

$\{V4\}$ at the lower level are merged in one subset $\{V2, V4\}$. In this case, the situation becomes safer than the previous one, as vessel V2 increases its velocity and so it can not be a drifting vessel. This can be a situation more desirable than the previous one. Accordingly, the human operator can perform some actions (e.g., contacting the commander of vessel V2) in order to modify the current situation for obtaining the projected one. As described in section IV-C, if we have a decisional attribute associated with the projected situations, it is possible to classify each group of vessels as being safe or not. This allows us to evaluate automatically the projected situations, helping the human operator in deciding which can be the best action to perform (e.g., "Will the vessel Vi be in a safe position?", "Can I maintain the current situation?"). Moreover, it is possible to use the data gathered by sensors in order to compute the situation at each time interval by supposing that some particular attribute may change.

V. Conclusion and Future Works

This work proposes a framework based on Rough Sets theory for representing situations, offering an interactive approach for reasoning on situations and obtain different perspectives on the elements of the environment. It supports and enhances the comprehension of the current situation and its possible evolutions, sustaining rapid decision making. In future works, we plan to evaluate the approach in wider and heterogeneous scenarios. Moreover, we will design interfaces and dashboards in which the users can interact with the lattices representing the identified situations. We plan to implement such interfaces to enhance decision support systems based on Situation Awareness in several domains, like logistic [16] and commerce [17].

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