Dissecting uncertainty-based fusion techniques for maritime anomaly detection

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***Abstract*—Detecting and classifying anomalies for Maritime Situation Awareness gets a lot of benefit from the combination of multiple sources, correlating their output for detecting inconsistencies in vessels' behaviour. Adequate uncertainty representation and processing is crucial for this higher-level task where the operator analyses information correlating with his background knowledge. This paper addresses the problem of performance criteria selection and definition for information fusion systems in their ability to handle uncertainty. Indeed, i addition to the classical algorithmic performances of accuracy or timeliness, other aspects such as the interpretation, simplicity, expressiveness need to be considered in the design of the technique for uncertainty management for a improved synergy between the human and the system. In this paper, we dissect several uncertainty representation and reasoning techniques (URRTs) addressing a fusion problem for maritime anomaly detection. The *uncertainty supports* are identified as a basis for the global *expressiveness* criterion. A selection of six elementary URRTs are described and compared according to their expressiveness power of uncertainty, using the Uncertainty Representation and Reasoning Framework (URREF) ontology. This study is considered as preliminary to guide further development and implementation of fusion algorithms for maritime anomaly detection, and the definition of associated criteria and measures of performance.**

Keywords: Anomaly detection; Information Quality; Uncertainty; URREF; Bayesian reasoning; Belief functions.

I. Introduction

In the field of Maritime Situation Awareness (MSA), detecting and classifying vessels' abnormal behaviour is a challenging and crucial task at the core of the compilation of the maritime picture [1], [2]. It requires not only to extract relevant contextual information as materialized by maritime routes or loitering areas for instance [3], but also real time monitoring of the maritime traffic by a set of sensors mixing cooperative self-identification systems (such as Automatic Identification System (AIS)) and non-cooperative systems such as coastal radars or satellite imagery to overcome the possible spoofing of AIS signal. In many cases, intelligence information is of great help to refine and guide the search in the huge amount of data to be processed, filtered and analysed.

The operator, not only needs to get the appropriate information with good quality to make his/her decision, but also needs to understand the underlying meaning of the information provided (its origin, how it has been obtained, processed, what was the context of its creation, etc). For instance, it is of great interest for the Vessel Traffic System (VTS) operator to understand how an anomaly detector came up with an alert: Which were the reference data? Which sources were processed? Was the information and associated uncertainty obtained in objective or subjective manner? Did the process considered the sources' quality and how? Was the contextual information considered? What is the meaning of the numerical value of the uncertainty output? What was the underlying logical reasoning providing the answer? Etc. Higher-order information quality is also required, such as probability maps about possible threats, supplemented by uncertainty assessments about the validity of the probability values, as intervals for instance, or error performance estimations on algorithms' performance. These information quality dimensions are increasing operator's trust and use of the system.

The standard performance criteria of algorithms such as precision, accuracy, False Alarm Rate, Area Under the Receiver Operating Characteristic (ROC) curve (AUC), or computational cost [4], [5], [6] may not be sufficient and should be complemented by others to account for the close interaction of humans with the algorithms. For instance, some criteria such as adaptability, simplicity, expressiveness need to be considered as well. The Evaluation of Techniques for Uncertainty Representation (ETUR) working group works for 4 years now to define and connect these criteria to the uncertainty models and frameworks, uncertainty types, uncertainty derivation, uncertainty nature [7]. Some outcomes of this work are guidance for the selection and design of adequate tools for reasoning support, uncertainty traceability and understandability (*e.g.* , [8], [9]). It is also a first step toward some standardization of the characterization and assessment of uncertainty management techniques and by extend, fusion algorithms.

In this paper, we propose to compare six (6) different approaches (hereafter called Uncertainty Representation and Reasoning Techniques, URRT) to fuse pieces of information from a set of heterogeneous sources (hard and soft) as the core of maritime anomaly detector for route deviation. In complement to comparative analyses as provided for instance in [10], [11], the aim of this paper is to provide other comparison elements which may have an impact on the behaviour (and performances) of the fusion scheme. In Section II, we briefly introduce the URREF ontology and introduce the *uncertainty supports* as part of possible refinement of the *expressiveness* criterion. The anomaly detection problem addressed here as a use case is presented in Section III and 6 URRTs are introduced in Section IV, as alternative schemes to solve the above defined problem, with an emphasized description of the uncertainty representation. The 6 URRTs are compared in Section V and assessed in a qualitative way regarding their expressiveness. We conclude in Section VI on future works and possible further challenges to be addressed in the coming years by the Uncertainty Representation Evaluation Framework working group.

II. Uncertainty Representation and Reasoning Framework (URREF)

The URREF ontology [7] identifies, defines and links uncertainty-related concepts which come into play when evaluating the uncertainty representation and reasoning approaches underlying any information fusion system. A complete description of the current state of the ontology is available at the ETUR working group collaboration web site[1], while we provide here a partial description focusing on the elements to be discussed in this paper.

The first level concept Thing is split into UncertaintyNature (epistemic vs aleatory), UncertaintyType, UncertaintyModel (mathematical framework), UncertaintyDerivation (objective vs subjective), EvaluationSubjects and associated EvaluationCriteria, and Source (of information).

We provide below a further description of EvaluationSubjects and focus on the EvaluationCriteria of Expressiveness under the RepresentationCriteria.

A. Evaluation subjects

Evaluation subjects are the elements composing the URRT which assessment through the URREF is meaningful [12]. An evaluation subject is any item which may have an impact on the system's output and can be made varying or exchanged, thus compared and assessed according to a series of corresponding criteria. A finer description and characterization of uncertainty handling in a fusion system would highlight other aspects when evaluating the fusion algorithm than the standard measures of performance. Indeed, the system could not only be assessed globally (based on its output) but also could each of its components, *support of uncertainty*, *modeling of uncertainty* (representation part) and *uncertainty calculus* (reasoning part).

Let h denote the uncertainty representation process taking as input some data over the observation space $\mathcal{X}$ and associated imperfection, captured and provided to the system by sources of information observing a particular real world situation. Let η denote the uncertainty inherent to the problem we attempt to model and to be captured by h. We distinguish between η^0, the prior uncertainty (without a specific distinction of the previous instants), and η^t, the uncertainty at time t, the time of the observation. The uncertainty η comes either from epistemic uncertainty (limited knowledge of the source) or from aleatory uncertainty (either from the real world process or from the source's process) referring to the UncertaintyNature. η denotes the uncertainty before it is even modeled within the system and can be expressed in natural language, with a score vector not within a mathematical framework yet, as a probability distribution with or without specific meaning, etc.

Let denote by γ the reasoning process taking as input the transformed input data from the different sources as represented by h and outputting an answer over a decision space $\mathcal{Y}$, capturing the user's needs and interest. The description of the reasoning part will not be address in this paper and will be further detailed in an extended version of this work.

[1] www.gmu.org/etur

B. Uncertainty supports

The uncertainty representation process h is the way by which the uncertainty is modeled, considered, quantified by the fusion system we design or analyse. It applies (1) to the observation space $\mathcal{X}$, either to model a new measurement or information, or some prior knowledge about the variables of $\mathcal{X}$, (2) over the decision space $\mathcal{Y}$ and (3) at the boundary between the two spaces, since the link between measurements and classes are also uncertain. We define the *uncertainty supports*, as items about which some uncertainty statement can be expressed and distinguish between:

- variables of $\mathcal{X}$, either considered individually X_i or jointly (X_i, X_j) ,
- variables of $\mathcal{Y}$, either considered individually Y_i or jointly (Y_k, Y_l),
- links between $\mathcal{X}$ and $\mathcal{Y}$, (X_i, Y_k),
- second-order uncertainty about any uncertainty expressed over the supports above.

TABLE I
Uncertainty supports and associated meaning.

Notation	Meaning	Example of elicitation
$\eta^0(X_i)$	Prior uncertainty about individual measurements	*Distribution of length values*
$\eta^0(X_i, X_j)$	Prior uncertainty about links between measurements	*Joint distribution of length and type*
$\eta^0(Y_k)$	Prior uncertainty about individual output classes	*Prior belief about a given route*
$\eta^0(Y_k, Y_l)$	Prior uncertainty about links between output classes	*If two routes share part of the trajectory*
$\eta^0(X_i, Y_k)$	Prior uncertainty about links between measurements and classes	*Distribution of speed given a specific route*
$\eta^0(\eta^0)$	Prior uncertainty about uncertainty expression (second-order uncertainty)	*Uncertainty on probabilistic model representing length distribution*
$\eta^t(X_i, Y_k)$	Uncertainty at t links between measurement and class	*Distance from measurement to prototype*
$\eta^t_s(X_i)$	Uncertainty at t about measurements by source s	*Score vector output by the ATR about the type*
$\eta^0(\eta^t_s)$	Prior uncertainty about source s quality (source's reliability)	*Confusion matrix of the ATR about vessel type*

In the case of second-order uncertainty, uncertainty representations are themselves uncertainty supports since for example, we may have some uncertainty about the "true" probability distribution for a given variable. For instance, using imprecise probabilities as an uncertainty representation model allows to account for this second-order uncertainty, and rather considers a set of probability distributions. Table I lists the uncertainty supports together with the notation, meaning and example.

In Table III, the URRTs are assessed according to their ability to capture the uncertainties of Table I.

The uncertainty representation h is assessed by the REPRESENTATIONCRITERIA of the URREF ontology.

C. Evaluation criteria

We focus on the EXPRESSIVENESS criterion, of the REPRESENTATIONCRITERIA group of the URREF ontology. Expressiveness is defined as the power of an uncertainty representation technique to convey relevant aspects of a given fusion problem [7]. We identify the uncertainty supports as "relevant aspects" of the problem as they are able to convey the idea of DEPENDENCY, HIGHER-ORDER UNCERTAINTY, (source) SELF-CONFIDENCE and extend to the source's reliability.

Moreover, we assess the uncertainty representation h, according to the the three information[2] quality dimensions of *uncertainty*, *imprecision* and *trueness*.

- *Uncertainty* - Refers to a degree of confidence assigned to a specific (or set of) value to be "true", while a single one is known to be true. Its cause can be either a lack of knowledge (epistemic uncertainty) or the random variability of the underlying process (aleatory uncertainty). When assigned by the source itself it may be called "self-confidence", but since we can also assess uncertainty at the output of the fusion process, we keep the general term of uncertainty;
- *Imprecision* - Refers a set of possible values, regardless how they have been obtained: The smaller the size of the set, the higher the precision. It represents the inability of the source to provide a single value or to discriminate between several values;
- *Trueness* - Refers the "closeness of agreement between the expectation of a test result or a measurement result and a true value" [13]. It is considered here as the criterion relating a piece of information (either input or data) to the truth or a reference value.

Usually, imprecision (or precision) and uncertainty are opposed [14]: "I'm certain that the speed of the vessel is between 3 and 6 knots" (Imprecise but certain statement) versus "I'm not certain that the speed of the vessel is 5 knots" (Precise but uncertain statement). On the other hand, precision and trueness are often associated in performance assessments of systems (gathered under the term *accuracy* in ISO 5725 [13]), referring to a series of independent tests.

The way these information quality dimensions relate to the concepts of UNCERTAINTYTYPES, UNCERTAINTYDERIVATION, DATACRITERIA is still under discussion within the ETUR working group.

III. MARITIME ANOMALY DETECTION PROBLEM

We consider a vessel V observed by a series of sources $\mathcal{S} = \{s_1, \ldots, s_N\}$ being possibly of different natures such as a coastal radar and its associated tracker, a SAR (synthetic Aperture Radar) image with associated ATR (Automatic Target Recognition) algorithm or a human analyst, a visible camera operated by a human analyst, AIS (Automated Information System) information send by the vessel itself, some intelligence sources, etc. We consider the problem of associating V to a route among a set of 5 pre-computed routes and detect possible abnormal behaviour. The AAP-6-2014 NATO glossary of terms defines a route as "*The prescribed course to be travelled from a specific point of origin to a specific destination*".

Let $\mathcal{A} = \{\text{POSITION}, \text{HEADING}, \text{SPEED}, \text{LENGTH}, \text{TYPE}\}$, be the set of features of interest to be observed by the set of sources, and let $\mathcal{X}$ be the corresponding observation space, built in our case from 5 variables corresponding to some vessel's attributes. We denote, for any $i \in \mathcal{A}$, by X_i the random variable associated to feature i, by $\mathcal{X}_i$ its associated domain of definition containing the set of its possible values, by $x_i \in \mathcal{X}_i$ and by $A_i \subseteq \mathcal{X}_i$, a subset of $\mathcal{X}_i$. Let us denote by $\mathbf{x}_t = \{\phi_{p,t}^{(s1)}; \phi_{\theta,t}^{(s2)}; \phi_{s,t}^{(s3)}; \phi_{l,t}^{(s4)}; \phi_{T,t}^{(s5)}\}$ a set of observations jointly provided by the set of sources about the attributes in $\mathcal{A}$. This notation covers the general case where sources are able to provide some uncertainty about their statement and thus ϕ denotes sources' statement either as a single measurement, a probability vector, a natural language declaration, etc. In the specific case of precise and certain measurements from the sources, $\mathbf{x}_t$ is a vector of $\mathcal{X}$. The superscript (s_i) denotes the source's index in $\mathcal{S}$ which provided the information. For the purpose of the discussion in this paper, we consider that each attribute is provided by a single source (while in general several sources provide information about the same attribute) and will thus omit the superscript. Moreover, we focus on the aggregation (fusion) of all observations obtained at the same instant in time t, and thus for the sake of simplicity, the index t will be omitted as well. Uncertainty about the state transition $\mathbf{x}_t \to \mathbf{x}_{t+1}$ will be considered in further extension of this work.

A route detector is designed to help the VTS (Vessel Traffic System) operator to (1) associate vessels to existing routes, and (2) detect abnormal behaviours to be further investigated. Among the numerous reasoning schemes solving that problem, we consider a quite simple one where an anomaly is detected based on a joint assessment (fusion) of the 5 features describing the routes. Other said, the behaviour of a vessel V is detected as being abnormal if the set of its 5 estimated features is not compatible with a route.

Let $\mathcal{R} = \{R_1, \ldots, R_K\}$ be a finite set of routes possibly followed by the vessel V for the given area of interest and let $\mathcal{Y}$ be the exhaustive set of corresponding labels where an additional label y_0 represents "none of the 5 routes", such that $\mathcal{Y} = \{y_0, y_1, \ldots, y_5\}$ where y_k is the label output by the fusion system corresponding to route R_k and y_0 is a "rejection class" corresponding to the abnormal behaviour. This class gathers the possible events of "The vessel is off-route", "The vessel is in reverse traffic on the route", "The speed is not compatible with the route followed", "The type of the vessel is not compatible with the route followed", which are some Maritime Situational Indicators of interest for the

[2]The term "information" is used here is a general way to cover other terms such as data or evidence.

VTS operator.

The fusion system to be designed aims at establishing a mapping $\Psi : \mathcal{X} \longrightarrow \mathcal{Y}$ from the observation space $\mathcal{X}$ to the decision space $\mathcal{Y}$ such that $\hat{y} = \Psi(\mathbf{x})$ is the route label assigned to the vessel V represented by the observation vector $\mathbf{x}$ at time t. The basic underlying reasoning scheme is that any observed feature is a contribution (positive or negative) to our belief that V is following a route from $\mathcal{R}$. Indeed, if all the observed features match a specific route, then the corresponding route label is assigned to the vessel. If some conflict exists between the set of observed features and the routes feature vectors, then V may be assigned to no route. Thus, it is possible that a vessel is detected to be physically on route R_1, while labeled y_0 meaning for instance that its type and length are incompatible with R_1's features.

IV. UNCERTAINTY REPRESENTATION AND REASONING TECHNIQUES

We consider here 6 different uncertainty representation and reasoning techniques (URRTs) as 6 instantiations of the fusion model Ψ, to be further assessed through the URREF. The URRTs presented here are very basic schemes far less complete than the ones reported in the literature addressing the problem of maritime anomaly detection. Rather, we provide here a simple presentation for a better understanding of the underlying reasoning, as a first step for comparison.

A. URRT1: Pattern matching - Euclidean

A standard pattern matching approach computes the Euclidean distances between $\mathbf{x}$ and each of the routes of $\mathcal{R}$ as:

$$\begin{aligned} d^{(E)}(\mathbf{x}, R_k) &= \sqrt{(\mathbf{x}-\mathbf{r}^{(k)})'(\mathbf{x}-\mathbf{r}^{(k)})} \qquad (1) \\ &= \sqrt{\sum_{i\in\mathcal{A}}(x_i - r_i^{(k)})^2} \end{aligned}$$

where $\mathbf{r}^{(k)}$ is the prototype corresponding to route R_k (see Section V-B), defined in the feature space $\mathcal{X}$ and $\mathbf{x}'$ is the transpose vector of $\mathbf{x}$. The i^{th} components of $\mathbf{x}$ and $\mathbf{r}^{(k)}$ are denoted by x_i and $r_i^{(k)}$ respectively. A vector of distances $\mathbf{d}$ is then built, its components $d_k^{(E)}$ being the distances from $\mathbf{x}$ to each R_k. The quantity $d_i^2 = (x_i - r_i^{(k)})^2$ can be interpreted as a *degree of match* of the observation of feature i to the route. The decision rule is:

$$\hat{y} = \begin{cases} \arg\min_k d^{(E)}(\mathbf{x}, R_k) \text{ if } d^{(E)}(\mathbf{x}, R_k) < \epsilon \\ y_0 \text{ else} \end{cases}$$

where ϵ is a threshold to be set according to the operator's needs or expectations, representing some tolerance over the global distance over the 5 features. Many anomaly detection approaches are based on distances computation as an implementation of the notion of "closeness to normalcy" (*e.g.* , [6]).

B. URRT2: Pattern matching - Malahanobis

A modified version of the Euclidean pattern matching scheme is obtained by using the Malahanobis distance:

$$d^{(M)}(\mathbf{x}, R_k) = \sqrt{(\mathbf{x}-\mathbf{r}^{(k)})'\mathbf{\Sigma}^{-1}(\mathbf{x}-\mathbf{r}^{(k)})} \qquad (2)$$

where $\mathbf{\Sigma}$ is the covariance matrix of the random vector $\mathbf{X}$ associated to $\mathbf{x}$, whose coordinates are r.v. X_is. The superscript $^{-1}$ denotes the inverse matrix. The element $\sigma_{i,j}$ of $\mathbf{\Sigma}$ is the covariance of X_i and X_j defined as $E(X_i, X_j) - E(X_i)E(X_j)$ where E is the expectation operator such that $E(X) = \sum xp(X = x)$ for a discrete random variable X or $E(X) = \int xp(x)dx$ for a continuous random variable. The same decision rule (2) than for the Euclidean pattern matching is used. However, the threshold ϵ can be set based on the covariance matrix.

The Euclidean and Malahanobis distances in (1) and (2) are well suited to features defined over numerical and continuous scales while they reduce to binary AND for nominal variables such as the type, for instance. Better suitable distance measures are usually used based on the aggregation of individual for each feature, possibly using different definitions than the square difference (*e.g.* , [15]). Other distances such as the log normal probability density (*e.g.* , [4]) would account for the route's statistics as well.

C. URRT3: Probability-based - Bayesian

In the standard Bayesian approach to fusion, the functions $p(X_i = x_i|R_k)$ for variables in $\mathcal{X}$ and routes in $\mathcal{R}$ represent the likelihood of observing a specific set of values $\mathbf{x}$ on a given route R_k, based on past information used to build the routes. The different features are combined following Bayes' rule:

$$P(R_k|\mathbf{x}) \propto p(R_k) \prod_{i\in\mathcal{A}} p(x_i|R_k), \forall R_k \in \mathcal{R} \qquad (3)$$

under the assumption of *independent features*. The resulting posterior probability $p(R_k|\mathbf{x})$ represents some belief that the route followed by the vessel V is R_k given that we observed $\mathbf{x}$. A normalization factor ensures that a probability distribution is obtained. The combination rule (3) can be written using the posterior probabilities as $P(R_k|\mathbf{x}) \propto p(R_k)^{(R-1)} \prod_i p(R_k|x_i)p(x_i)$. The decision rule is the Maximum A posteriori Probability (MAP):

$$\hat{y} = \begin{cases} \arg\max_k p(R_k|\mathbf{x}) \text{ if } p(R_k|\mathbf{x}) > \tau \\ y_0 \text{ else} \end{cases} \qquad (4)$$

where threshold τ is set to meet the operator's needs: if the posterior probability is too uniformally distributed among the routes, then no clear matching is detected and an anomaly is returned. The Bayesian reasoning scheme is at the basis of the Bayesian network approach proposed for instance in [16].

D. URRT4: Probability-based - Non-Bayesian

In a non-Bayesian approach, each measured feature is considered providing some information (or evidence) about the membership of $\mathbf{x}$ to a given class R_k. For instance, $p_s(R_k) = p(R_k|x_s)$ is the contribution of the speed estimation to the membership of V to R_k and is interpreted as the probability that V belongs to R_k given (according to) the estimated speed. Then, the observations are aggregated by a weighted sum as:

$$p(R_k|\mathbf{x}) = \sum_{i\in\mathcal{A}} \omega_i p(R_k|x_i) \qquad (5)$$

where $\omega_i \in [0,1]$ is a weight reflecting the confidence in the soft decision values computed by the individual sources, and can be deduced from $p(x_i)$. This rule is derived in [17] from (3) under the assumption of equal $p(R_k)$. The decision rule is then (4).

E. URRT5: Transferable Belief Model (TBM) model-based

The reasoning scheme considered here is the one proposed in [18], [19] within the Transferable Belief Model (TBM) framework and making use of the Generalized Bayes Theorem (GBT) [20] as the combination rule:

$$\mathrm{Pl}(A|\mathbf{x}) = 1 - \prod_{R_k \in A} (1 - \mathrm{Pl}(\mathbf{x}|R_k)), \forall A \subseteq \mathcal{R} \tag{6}$$

where $\mathrm{Pl}(A) = \sum_{A \cap B \neq \varnothing} m(B)$ is the plausibility of $A \subseteq \mathcal{R}$, with m being a Basic Belief Assignment (BBA) such that $\sum_{A \subseteq \mathcal{R}} m(A) = 1$. $\mathrm{Pl}(A|\mathbf{x})$ is the conditional plausibility of A and is interpreted as the maximum confidence that can be assigned to A (*i.e.* , that the route followed belongs to the subset A) given that $\mathbf{x}$ has been observed. As proposed in [18], $\mathrm{Pl}(\mathbf{x}|R_k)$ is the least committed plausibility function corresponding to the probabilistic likelihood function considered as the pignistic probability. For a BBA m, the pignistic probability is defined for any singleton of $\mathcal{R}$ as $\mathrm{BetP}(R_k) = \sum_{R_k \in A} \frac{m(A)}{|A|}$. The decision rule requires then two steps: (1) the transformation of the Pl measure into a probability distribution over $\mathcal{R}$ (such as the pignistic probability) such that (2) then the MAP rule (4) can be applied.

F. URRT6: Belief functions-based - Database query

Similarly to the probabilistic non-Bayesian URRT4, each observed feature x_i of $\mathbf{x}$ is assumed to provide some evidence about route R_k being the route followed by V. The uncertainty is modeled by belief functions rather than by posterior probabilities.

Each observation x_i is regarded as a query to $\mathcal{R}$ such that only the items satisfying the associated criterion are retrieved, to form a set of possible routes A_i. For instance, A_1 is the set of routes compliant with a measured speed of 5 knots. Then, some uncertainty is assigned to this set under the form of a BBA m_i over $\mathcal{R}$. While A_i is the set of routes satisfying the query ($A_i = \{R \in \mathcal{R} | x_i \in R(i)\}$), its numerical weight $m_i(A_i)$ is interpreted as the degree of belief that can be assigned to A_i and none other subset of A_i. For instance, let $\phi_T = [0.4\ 0.3\ 0\ 0.3\ 0]'$ be the uncertainty regarding the type of the vessel output by the source. Then, $A_{\text{Cargo}} = (R_1, R_2, R_3, R_4, R_5)$ is the set of routes possibly followed by cargo vessels and is assigned a weight of 0.4, $A_{\text{Tanker}} = (R_2, R_3, R_5)$ and $m(A_{\text{Tanker}}) = 0.3$ and $A_{\text{Passenger}} = (R_2, R_5)$ and $m(A_{\text{Passenger}}) = 0.3$. This multivalued mapping does not define a probability distribution over $\mathcal{R}$ but a BBA since $m_i(A) \neq 1 - m_i(\overline{A})$.

The resulting BBA m over $\mathcal{R}$ is obtained by combining the individual contributions of each feature by the conjunctive rule, where weights are assigned to conjunctions of sets of routes A_i and A_j:

$$m(A) = \sum_{A_i \cap A_j = A} m_i(A_i) m_j(A_j), \forall A \subseteq \mathcal{R} \tag{7}$$

The decision rule is similar to (8) but considers the conflict measure as a criterion for anomaly:

$$\hat{y} = \begin{cases} \arg\max_k \mathrm{BetP}(R_k) \text{ if } m(\varnothing) < \beta \\ y_0 \text{ else} \end{cases} \tag{8}$$

where BetP is the pignistic transformation of m. The quantity $m(\varnothing)$ is the BBA of the empty set after combination and represents the global weight of conflict between all the sources. If they agree on at least one route to be the followed by V, then $m(\varnothing) \neq 0$. The threshold β is set according to the user's needs.

V. Assessment of URR techniques

To characterize the different approaches for a better understanding, to guide the design of anomaly detectors, and to ultimately select the most appropriate solution to the given problem of maritime anomaly detection, we illustrate how the URREF and its associated criteria ontology can be used.

A. Elements of the observation space

The basic domains for variables represent user's needs and interest and are considered constant for the 6 URRTs, although they could have been set differently. Also, we consider that the sources directly report on these domains. The 6 domains are listed in the first rows of Table III.

B. Uncertainty in the decision space

The set of routes is previously extracted based on a large number of AIS tracks for the given area, as described in [3] and illustrated in Figure 1. Each route is represented in a synthetic

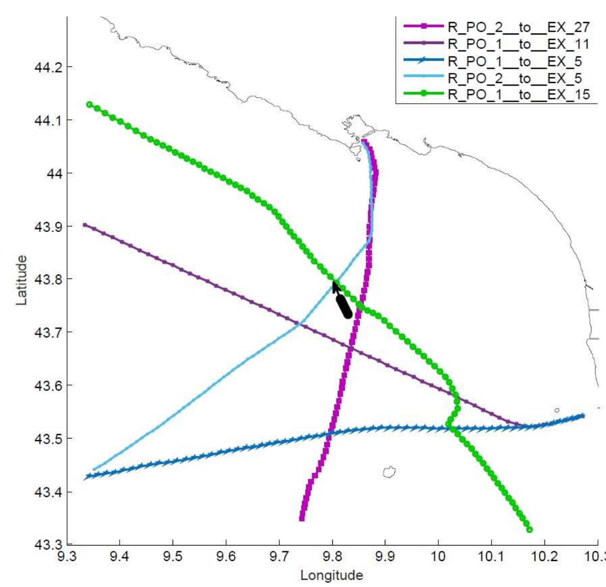

Fig. 1. Set of routes for the given area under observation.

TABLE II
DICTIONARY OF ROUTES AND ASSOCIATED UNCERTAINTY REPRESENTATION.

Route	Name	Synthetic route	Traffic information			
		POSITION	COURSE	SPEED	LENGTH	TYPE
		$\{(p_i^{(k)}, \theta_i^{(k)})\}_{i=1}^N \pm w^{(k)}$	$\mu_\theta \pm 2\sigma_\theta$	$\mu_s \pm 2\sigma_s$	$[l_{\min}; l_{\max}]$	p over $\mathcal{T}$
R_1	RP02toEX5	$\{WP\}^{(1)} \pm$ 5km	210 $\pm 25°$	$\mathcal{N}(11, 2)$	[80; 200]	[1 0 0 0 0]
R_2	RP01toEX3	$\{WP\}^{(2)} \pm$ 2km	245 $\pm 30°$	$\mathcal{N}(12, 3)$	[20; 170]	[0.43 0.43 0.05 0.05 0.04]
R_3	RP01toPO4	$\{WP\}^{(3)} \pm$ 1km	280 $\pm 30°$	[2; 16]	[20; 290]	[0.5 0.5 0 0 0]
R_4	RP02toEX27	$\{WP\}^{(4)} \pm$ 4km	185 $\pm 10°$	[10; 16]	[20; 230]	[0.75 0 0 0 0.25]
R_5	REN1toEX15	$\{WP\}^{(5)} \pm$ 1.5km	325 $\pm 20°$	$(\mathcal{N}(12, 2); \mathcal{N}(19, 2))$	[110; 200]	[0.67 0.11 0 0.11 0.11]

way by a series of waypoints with associated headings. Other attributes characterizing the kind of traffic of the route about the vessels traveling on this route are added such as the speed, length and type of vessels.

Routes are extracted by clustering a large amount of trajectories gathered from AIS signals and synthesize the maritime traffic observed in the past for the given area. By nature, routes are ill-defined objects, and their uncertainty characterization and representation is of prime importance for a proper consideration in the anomaly detection procedure. Figure 2 is an example of the route characterization of uncertainty that has been used to built the dictionary of routes of Table II. Each

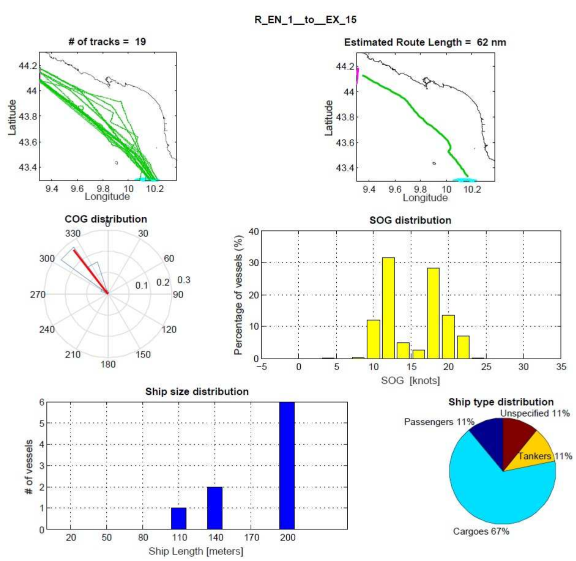

Fig. 2. Statistics from route extraction as a basis for uncertainty representation.

route is represented by a prototype $\mathbf{r}^{(k)}$ which features are *precise* and *certain* values corresponding for instance to the mean or mode of the corresponding distributions. However, some *imprecision* or *uncertainty* information about routes can be extracted based on the statistical information from the raw AIS dataset for a richer representation. For instance, the route width w_k is an *imprecision* parameter defined as the average distance between the minimum and maximum distance to the mean trajectory (waypoints) along the route. It is extracted from raw data and defines an area where the vessels have been observed in the past.

The statistics extracted from the raw AIS dataset serve as the basic ingredient for both (1) the uncertainty representation about the route objects and (2) the uncertainty about new measurement. The histogram of the different attributes (Speed Over Ground (SOG), Course over Ground (COG), Length, Type) are further interpreted as likelihood functions $p(X_s = s|y_k)$ and approximated by different models.

For instance, the speed attribute for Route R_1 can defined by the couple $(\bar{s}_1; \sigma_1^{(s)})$ representing the mean and variance of speed values estimated on the training data set of trajectories used to build R_1. Another representation could be $(\bar{s}_1; \pm\sigma_1^{(s)})$ defining a range of acceptable values to decide that the observed speed of the vessel corresponds to R_1. A Gaussian or a Mixture-of-Gaussian (MoG) model could be used as well for the conditional likelihoods of the SPEED and LENGTH for instance. Then we could have either $p(X_s|R_k) = \mathcal{N}(\mu_s^k; \sigma_s^k)$ or $p(X_s|R_k) = \sum_{j=1}^m \alpha_k \mathcal{N}(\mu_s^k(j); \sigma_s^k(j))$.

The impact of such alternative representations on the answer provided by the system could be assessed then through the URREF, but the representation will be considered fixed in this paper. We rather focus on the ability of the URRT to capture or account for this uncertainty (expressiveness criterion).

C. URRTs analysis and comparison

Table III summarizes the comparative description of the 6 URRTs presented in Section IV as candidate solutions to the same problem of maritime route detection. The expressiveness of the URRTs relatively to the different uncertainty supports identified in Section II-B is first assessed in a binary way, so that "No" means that the technique does not account for the uncertainty on the corresponding support. Then, the quality dimension (*trueness*, *uncertainty*, *imprecision*) considered together with the uncertainty function are mentioned in case the URR technique does. The meaning of the different uncertainty supports listed in the first column are given in Table I. The corresponding criteria of the URREF ontology are mentioned in italic, highlighting possible extension of the URREF ontology to cover all the uncertainty supports.

We observe that the standard pattern matching approach (URRT1) does not account for any uncertainty support: The route representation is considered as precise and certain, as the prototypes are defined by single values (either the mean or the mode, for the type); the dependency between variables is not considered, nor is the possible links between routes; sources' uncertainty (or self-confidence) about their declaration is not considered; sources' reliability is not represented, nor any second-order uncertainty. The only information quality dimension considered is the trueness through the distance measure, the route prototype being considered as a reference:

TABLE III
EXPRESSIVENESS POWER COMPARISON OF UNCERTAINTY REPRESENTATION AND REASONING TECHNIQUES.

	URRT Name	URRT1	URRT2	URRT3	URRT4	URRT5	URRT6
	Mathematical framework	Geometry	Geometry, Statistics	Probability, Bayesian	Probability, Non-Bayesian	Evidence theory, TBM	Evidence theory
Domains	$\mathcal{X}_1$	$\{C_1, \ldots, C_{10000}\}$					
	$\mathcal{X}_2$	$\{[0;8],]8;15],]15;100]\}$					
	$\mathcal{X}_3$	$\{N; NW; W; SW; S; SE; E; NE\}$					
	$\mathcal{X}_4$	$\{[0;20],]20;50],]50;400]\}$					
	$\mathcal{X}_5$	$\{Cargo; Tanker; Fishing; Passenger; Others\}$					
	$\mathcal{R}$	$\{R_1, R_2, R_3, R_4, R_5\}$					
		EXPRESSIVENESS					
Uncertainty supports (see Table I)	$\eta^0(X_i)$	No	Imprecision $E(X_i^2)$	No	No	No	No
	$\eta^0(X_i, X_j)$ *Dependency*	No	Uncertainty $E(X_i, X_j)$	No	No	No	No
	$\eta^0(R_k)$	No	No	Uncertainty $p(R_k)$	No	No	No
	$\eta^0(R_k, R_l)$	No	No	No	No	No	No
	$\eta^0(X_i, R_k)$	No	No	Uncertainty $p(x_i \mid R_k)$	Uncertainty $p(x_i \mid R_k)$	Uncertainty $\mathrm{Pl}(\mathbf{x} \mid R_k)$	Imprecision $A \subseteq \mathcal{R}$
	$\eta^0(\eta_s^t)$ *Source' reliability*	No	No	No	Trueness + Precision $p(\hat{x}_i \mid x_i)$	No	No
	$\eta^0(\eta^0)$ *Higher-order uncertainty*	No	No	No	No	Imprecision $[\mathrm{Bel}(A); \mathrm{Pl}(A)]$	Imprecision $[\mathrm{Bel}(A); \mathrm{Pl}(A)]$
	$\eta_s^t(X_i)$ *Source' self-confidence*	No	No	No	No	No	Uncertainty ϕ_i
	$\eta^t(X_i, R_k)$	Trueness $d(x_i, r_i^{(k)})$	Trueness $d(x_i, r_i^{(k)})$	Uncertainty $p(R_k \mid \mathbf{x})$	Uncertainty $p_i(R_k)$	Uncertainty + Imprecision $\mathrm{Pl}(R_k \mid \mathbf{x})$	Uncertainty + Imprecision $m_i(A)$

the distance to a route can be interpreted as a degree of closeness between $\mathbf{x}$ and R_k.

The extension of URRT1 using the Malahanobis distance accounts for both the spread of the routes along the different features (through the individual standard deviations σ_is) and the dependency between variables (through the covariances $\sigma_{i,j}$s). The variance can be interpreted as a measure of imprecision regarding measure x_i. The covariance could be interpreted as some uncertainty about the link between X_i and X_j: The higher the correlation between variables, the lower the uncertainty of one variable given the other. Thus URRT2 accounts for prior uncertainty of each measurement through a statistical measure of imprecision for the distribution of X_i as well as for the possible statistical dependency between variables of $\mathcal{X}$.

The independence assumption still applies to the Bayesian approach of URRT3. No consideration for either source's reliability nor self-confidence as the measurement itself is assumed as both certain and precise by the source. Rather the uncertainty is described at the mapping between $\mathcal{X}$ and $\mathcal{R}$ where the likelihood $p(x_i|R_k)$ describes how probable is to obtain a given measurement provided that the vessel followed a specific route. Prior uncertainty about routes is explicitly considered by $p(R_k)$, and could be based on other contextual information such as meteorological or seasonal. Including source's reliability about measurements is a direct extension (see for instance [21]), as well as considering the dependencies. The aggregation is done through a product operator which has the drawback of decreasing very rapidly to 0 once one of the likelihood is very low.

In the probabilistic non-Bayesian approach of URRT4, the individual likelihoods are multiplied, and the higher the likelihood according to each feature, the higher the posterior. URRT4 does not consider the dependency between features, but although the independence assumption between features is in this case wrong, this naive Bayesian fusion rule is however shown to provide good (accurate) results. This can be explained by the randomness of likelihood estimates, the low variance mitigating the obvious bias [22].

URRT5 may be seen as an extension of URRT3 within the TBM model, where non-additive functions (*i.e.* , plausibility) are used rather than probabilities. Equation (6) is obtained under the assumption of a vacuous prior on $\mathcal{R}$, meaning that no prior information on routes is considered. The plausibility function $\mathrm{Pl}(\mathbf{x}|R_k)$ models some imprecision about the precise likelihood function $p(\mathbf{x}|R_k)$ used in URRT3. The output of the GTB being also a plausibility function, assigns plausibility values to *subsets* of $\mathcal{R}$, defining then a second-order uncertainty by means of a couple plausibility-belief measure expresses some uncertainty about the posterior event $R_k|\mathbf{x}$. This second-order uncertainty is not considered in the traditional Bayesian approaches where the probability estimations are considered certain. Other equivalent approaches exist framed into imprecise probability or robust Bayesian.

In URRT6, the uncertainty output by the source about the measurement provided is considered. Rather than a single (precise and certain) measure, each source outputs a probability distribution over the set of values of their respective feature which induces as many multivalued mappings over $\mathcal{R}$ when querying the dictionary of routes. The prior uncertainty on the links between $\mathcal{X}$ and $\mathcal{R}$ is characterized as sets of routes (imprecision) satisfying some criteria about the features. This is further combined with the uncertainty of the source at time t, expressed by ϕ_i which induces the resulting BBA. The characteristic of this scheme is to deal with subsets of routes, in a qualitative way, with an additional quantification.

Each of the URRT above could be improved to account for the reliability of the sources (using the discounting operation for belief functions for instance [23] in URRT6, or as proposed in [21] for extending URRT3), for the prior, etc. Extended work will cover this aspect.

VI. Conclusions and future works

In this paper, we proposed a detailed description and comparison of 6 uncertainty and reasoning techniques (URRTs) to information fusion in their ability to handle uncertainty. The different schemes all solve the same problem of maritime route and detection through different uncertainty handling approaches. The elements of expressiveness are derived within the observation and decision space, the junction between both as well as second-order uncertainty. Through the identification of the *uncertainty supports*, the URRTs have been shown to account for uncertainty about distinct variables making use however of the same basic ingredient of likelihood functions, for instance. This should warn the designer on the need of careful handling of uncertainty. In particular, if the elicitation of prior uncertainty is based on the same data than the ones used to build the routes, then some uncertainty maybe counted twice within the system and the result may be biased.

The expressiveness criterion should not be assessed in isolation and it is only the joint assessment of the various criteria which make the URREF valuable. Indeed, as exemplified by the non-Bayesian probabilistic rule (URRT4), a lack of expressiveness about the dependency, may improve the overall accuracy of the algorithm through some natural balance process.

Rather than identifying a "winner" approach, the comparison between URRTs presented aimed at highlighting the *differences* and possible *complementarity* in uncertainty representation and expressiveness. Each of the basic schemes presented here can be enriched to account for more uncertainty supports, for a richer expressiveness. In future works we will develop these ideas trying to enrich each model with the elements of the others and characterize their possible limitations, if any. Also, through the implementation of the different schemes, we will evaluate their performances on series of test along the criteria of precision and trueness (accuracy), timeliness, computational cost.

Acknowledgments

The authors wish to thank the NATO Allied Command Transformation (NATO-ACT) for supporting the CMRE project on MSA.

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