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Uncertainty evaluation of data and information fusion within the context of the decision loop

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Abstract—**In this paper, the principle taxonomy of the fusion process, the decision loop, is unified with uncertainty quantification and representation. A typical flow of information in the decision loop takes the form of raw information, uncertainty modelling, combination, and decisions, which corresponds closely with Boyd's Observe, Orient, Decide and Act or OODA loop. The uncertainty associated with modelling during fusion system design was considered in previous works by the authors of this paper. Here, the uncertainties in the combination and decision parts of the information flow are considered. The objective of this paper is to make explicit how uncertainties that arise during design, combine with uncertainties during runtime, as well as the effect these uncertainties have on the ultimate decisions. The uncertainty representation and reasoning framework (URREF) ontology can only be meaningfully used for evaluation when the subjects of evaluation within the fusion system, and more broadly the decision loop, are defined explicitly.**

I. Introduction

Information fusion utilises key contributions from Bayes, Gauss, Pearson, and Kalman as applied from observed data to streaming messaging. A fundamental concept is the decision rendered from the analysis of these techniques [1]. Bayes rule is a probability update between competing entities. The Gaussian distribution provides an uncertainty model that affords a reduction in uncertainty when different sources of information are combined. Pearson's correlation coefficient determines the quality of a decision. Finally, the Kalman filter provides the ability for time varying stream processing. In the information fusion community, there are three types of common applications: object/target tracking [2], sensor management [3], and situation/threat assessment [4], which require decision loops.

The current trends in information fusion design and analysis seek to bring together methods and algorithms with applications to support and enhance decision making. Typically, the focus for information fusion was on the design of the tracking and filtering methods to reduce uncertainty [5] given models and design frameworks [6]. These machine-based systems rely on the models and sensed-data available to reason about situations. If data and information were able to support contextual reasoning [7], uncertainty analysis would be needed for many types of models from cognitive, information, and physical domains. One such example of an application of information fusion technologies is in disaster response [8], a decision process which requires the fusion of many data types in real time for efficient communication, effective response, and accurate human interpretation.

In the design of an information fusion system, the premise is that the fusion system designer would like to isolate and model some part of the real world through processes of abstraction. This model will be used to combine information from human (soft) and sensor (hard) sources in order to make decisions, and influence the outcome of the part of the world through decisions and actions. A previous paper [9] by the authors, considers where uncertainties enter the fusion systems *by design*. These uncertainties are combined with uncertainties of the sources and fusion algorithms *at runtime*, to result in inferences and decisions with their own uncertainties at the output of the fusion system. Finally, there are uncertainties on how certain decisions and actions will affect the real world.

In contrast with [9], which considers uncertainties that enter during design and modelling, the objective of this paper is to make explicit the uncertainties that enter at runtime during the process of information fusion and decision making. As such, by making the flow of information (and uncertainties) explicit, it is possible to systematically define the subjects of evaluation, upon which the evaluation criteria for the uncertainty representation and reasoning framework (URREF) [10], [11] can be applied. The rest of the paper is organised as follows: Section II describes the fusion loop using the OODA model. Section III presents two use cases of multi-radar tracking and rhino poaching prevention. Section IV aligns the decision uncertainty with the URREF. Section V lists the conclusions.

II. The Fusion Loop

Consider Fig. 1. This figure depicts the *flow of information* in a fusion system, and is in contrast to [9], which depicts the *flow of abstraction* during the process of modelling. The objective of making this flow of information explicit, is to properly define different subjects of evaluation in the information fusion process, as well as the uncertainties that flow through them. The ultimate goal of a fusion system is

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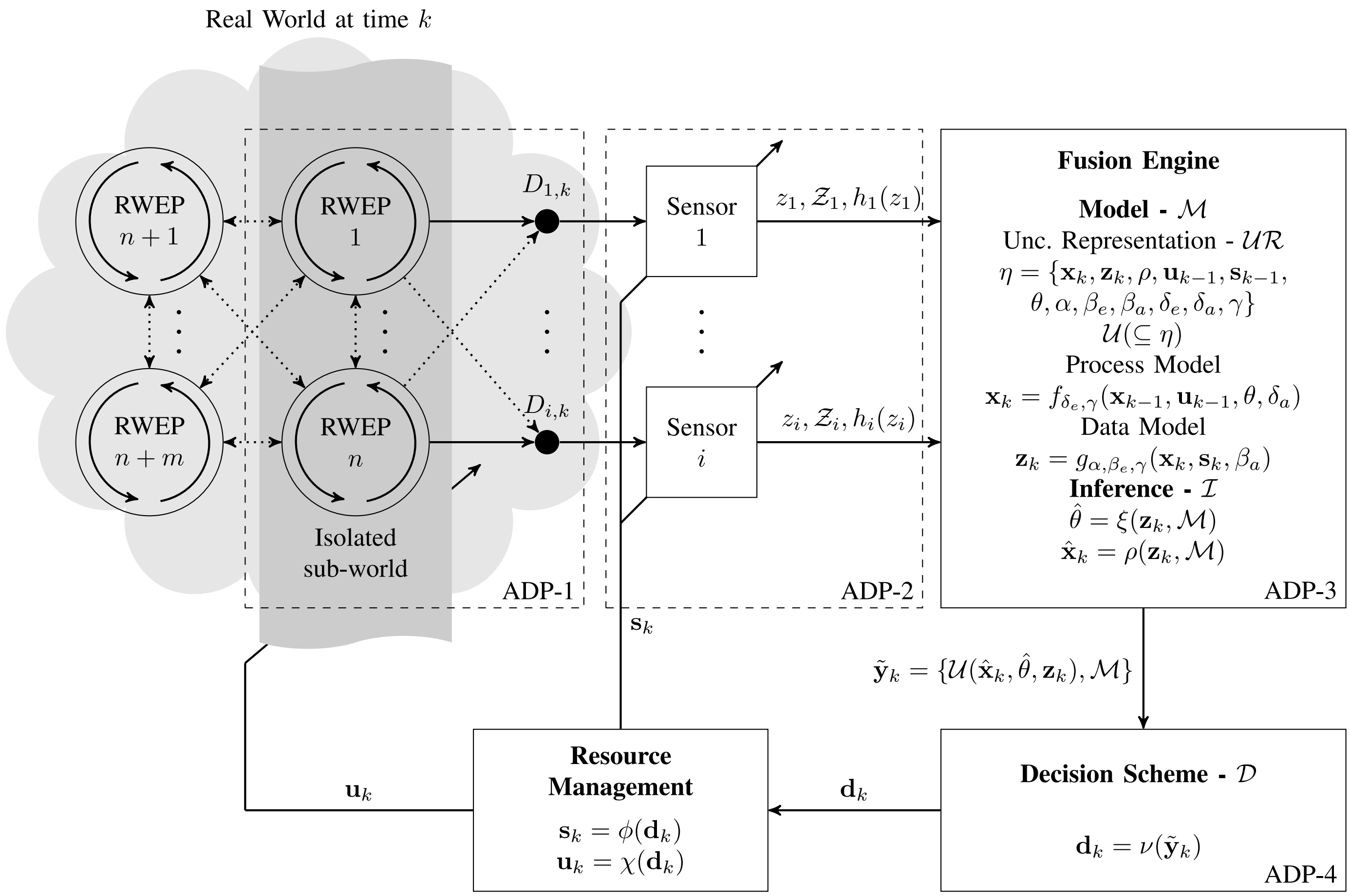

Fig. 1: The fusion loop.

to reduce uncertainty for the purpose of decision making. The information flow of the fusion process is organised according to the observe, orient, decide and act (OODA) loop of Boyd [12].

A. Observe

The first component of the OODA loop is "Observe" which utilises the premise that "all decisions are based on observations of the evolving situation tempered with implicit filtering of the problem being addressed" [12]. Observations originate from the real world, which is indicated by the light grey cloud in Fig. 1. As in [9], the world consists of real world entities and processes (RWEPs) that interact. These interactions are indicated by the dotted arrows. Consider an isolated part of the real world, which is of interest for the purpose of modelling, data and information fusion and ultimately making decisions. The isolated real world is indicated by the darker grey vertical tape. The nth RWEP of interest generates a datum $D_{i,k}$.

In the context of the Fusion loop in Figure 1, $D_{i,k}$ represents a set of observable effects from *all* RWEPs that can be observed by the ith sensor at time k – for example all targets that that can be observed by some radar. Although not indicated in the diagram for the sake of brevity, the nth RWEP has physical properties that can be represented by $\Omega_{n,k}$. The datum $D_{i,k}$ is conditioned upon $\omega_i \subseteq \{\Omega_{1,k}, \ldots, \Omega_{n,k}\}$ since the observable datum depends on the properties of the physical entities which sensor i can observe. Consequently the datum given its physical properties is written as $\{D_{i,k}|\omega_i\}$ or $D_{i,k}$ *given* ω_i. This is in contrast to the explanation in [9] where, as a simplifying assumption, the datum of the nth process was shown to depend only on Ω_n. The RWEPs and the data they generate correspond to the first stage of the Atomic Decision Process (ADP-1) in the taxonomies of [13], [14] and [15], corresponding to the *sources of information* of the fusion system.

As mentioned in [9], a datum may not only be an observation or measurement; it can also be an observable effect that has not been transduced into measured data, for example analog or digital voltages. Examples include electromagnetic scattering, natural language statements as well as ocean and air currents. It can also take the form of processed information such as mathematical statements or electronic data with some measures of uncertainty from computing systems or humans *outside* of the fusion system, whereas such humans or systems can also be represented by RWEPs.

The data $\{D_{1,k}, \ldots, D_{n,k}\}$ are transduced by sensors 1 to i into mathematical representations, which not only represent

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the quantities themselves, but also the uncertainties associated with such quantities. These quantities are represented in the figure by z_1 to z_i, along with their uncertainty representations $\mathcal{Z}_1$ to $\mathcal{Z}_i$, and uncertainty supports $h_1(\cdot)$ to $h_i(\cdot)$. Examples for quantities include integers, real numbers, vectors, complex numbers, tensors, norms, logic expressions *etc*. Examples for uncertainty representations include probabilistic, evidential or fuzzy representations; and examples of uncertainty supports include probability density functions, belief functions or fuzzy membership functions. The measurements of all sensors at time k are collected together in a variable $\mathbf{z}_k$ and their uncertainty supports in $\mathbf{h}$. Sensors here are defined rather broadly as transducers, humans that enter language statements into a computer, and also communication channels from other fusion systems, along the lines of the distributed fusion architectures of [16], [17]. The measurement process corresponds to the *uncertainty representation process* in [13], otherwise known as ADP-2.

B. Orient

The Orient part of the OODA loop serves "as the repository of our genetic heritage, cultural tradition, and previous experiences" [12]. As such it contains the model (our understanding) of the way the world functions, and is based on general mathematical knowledge of the behaviour of the sub-world. The fusion engine is the manifestation of this model of the world. More specifically, this system contains mathematical models and algorithms for the purpose of data association, data and information fusion, and inference.

1) Model: Although not explicitly shown in Figure 1, the overarching model $\mathcal{M}$ consists of several sub-models for RWEPs (object models), models for groups of RWEPs (situation models) and models for their current and future impact (impact models). Object models are used for object assessment in Joint Directors of Laboratories (JDL) level 1 data fusion taxonomy[18], [19], [20], [21]; situation models are used for situation assessment in JDL level 2; and impact models are used for impact assessment in JDL level 3. These levels also exist in the more recent and updated Data Fusion Interest Group (DFIG) taxonomy [21]. All these models at various levels of the JDL/DFIG taxonomy are therefore assumed to be encapsulated by the model $\mathcal{M}$. The measurements and/or observations are represented by $\mathbf{z}_k$, which is a collection of quantities and associated uncertainty supports $\mathbf{h}$ that are a direct result of some sensor transfer functions acting on real world data $\{D_{i,k}\}$. The quantity $\mathbf{z}_k$ is typically sub-partitioned, where subsets of $\mathbf{z}_k$ are associated with specific inferred RWEPs in a process commonly known as data association, although random set methods [22] do not require this step. Groups of RWEPs and interactions between them are associated with known situations during the process of situation assessment. In impact assessment, situations are associated with current and future costs or rewards.

In the taxonomy of figure 1, a distinction is made between *physical models*, which explain RWEPs and the data, and *uncertainty models*, which represent uncertainties that enter

TABLE I: Table of variables representing currently known forms of uncertainty that enter or exist within the fusion system (the elements of η)

Uncertain variable	**Description**
$\mathbf{x}_k$	State at time k
$\mathbf{z}_k$	Measurement at time k
ρ	Measurement conversion uncertainty (second order uncertainty)
θ	Parameters of process model
$\mathbf{s}_k$	Sensor controls at time k
$\mathbf{u}_k$	Mission controls at time k
α	Datum abstraction variable
β_e	Epistemic data model variable
β_a	Aleatoric data model variable
δ_e	Epistemic process model variable
δ_a	Aleatoric process model variable
γ	Isolation abstraction variable

into the fusion process. As already mentioned, uncertainty can enter the fusion process during design or during runtime. The physical models consist of a process model $f(\cdot)$ and a data model[1] $g(\cdot)$, which are characterised by uncertainties during modelling, and encompasses several processes of abstraction as explained in [9]. A discussion on the uncertainty representation $\mathcal{UR}$ follows, after which the effect of these uncertainties upon the physical models $f(\cdot)$ and $g(\cdot)$ are discussed.

2) Uncertain variables: Consider an explicit set η of all known variables (see Table I) that are characterised by uncertainty. The first, second and third components of η are the hidden state $\mathbf{x}_k$ of the process model to be inferred, the uncertain measurement $\mathbf{z}_k$, and the process model parameters θ. The uncertainty representation $\mathcal{U}(\mathbf{z}_k)$ is the internal representation of $\mathbf{h}(\mathbf{z}_k)$, which are the uncertainties fed from external sources/sensors. As such a conversion from the external uncertainty representation $\mathcal{Z}i$ and support $h_i(\cdot)$ of the data to an internal representation $\mathcal{UR}$ support $\mathcal{U}(z_i)$ is implied. The uncertainty associated with converting an external uncertainty representation to an internal representation (for example a vague language statement to a belief function) is denoted by ρ. This is a *second order uncertainty*, since it is uncertainty about the internal uncertainty representation $\mathcal{UR}$'s ability to represent $\mathcal{Z}_i$. The uncertainties surrounding the sensor control $\mathbf{s}_k$ and the mission control $\mathbf{u}_k$ may pertain to uncertainties of how controls influence the real world. The following subsections explain the components of η that follow from the modelling (abstraction) processes.

1) Datum abstraction: The component α is the datum abstraction uncertainty, and represents the uncertainty associated with converting a real world datum $D_{i,k}$ to some mathematical quantity $\mathbf{z}_k$. It is of an epistemic nature.
2) Data generation abstraction: The component $\beta = \{\beta_e, \beta_a\}$ is the data generation uncertainty, and it represents uncertainty about how data is generated by the

[1]also known as a measurement or observation model

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RWEP, as well as which RWEP generated the data. As such, it represents uncertainty about the model of data generation as well as uncertainty about the data association process. Refer to [22] and [9] for an explanation of the ambiguities related to data generation. Data generation uncertainty can be epistemic β_e or aleatoric β_a in nature; epistemic if the process of generating data (the data model) is poorly understood, and aleatoric if the data source is "noisy".

3) Process abstraction: The component $\delta = \{\delta_e, \delta_a\}$ denotes process uncertainty and represents uncertainty about the process model $f(\cdot)$, which in turn is a proxy for RWEPs. The symbol both represents uncertainty about the fidelity of the model (epistemic uncertainty δ_e) as well as uncertainty about inherent randomness within the evolution of an RWEP (aleatoric uncertainty δ_a).
4) Isolation abstraction: Finally, a complete model should also represent the uncertainty associated with isolating a part of the real world for the purpose of making inferences and decisions, and hence ignoring the effects of RWEPs $n+1$ to $n+m$. This isolation uncertainty is represented by the symbol γ.

3) Second order uncertainty: There will be uncertainty about whether the uncertainty representation $\mathcal{UR}$ and its corresponding support $\mathcal{U}$ adequately represents all the uncertainties listed in Table I. This is a second order uncertainty (uncertainty about uncertainty) and can impossibly be represented within the model $\mathcal{M}$, since it involves a shortcoming of the uncertainty representation $\mathcal{UR}$.

4) Internal uncertainty support: A fusion system will typically have an internal uncertainty support $\mathcal{U}$ of a subset of the uncertainties listed in η. The notation $\mathcal{U}(\eta)$ indicates as the most general case a *joint uncertainty support* over all uncertain variables in the fusion engine. An example is a joint probability distribution if the uncertainty representation is probabilistic. At the very least, most Bayesian fusion systems will represent an uncertainty support over inputs $\mathbf{x}_k, \mathbf{z}_k, \beta_a$ and δ_a and outputs $\hat{\mathbf{x}}_k, \hat{\theta}$, i.e. $\mathcal{U}(\mathbf{x}_k, \mathbf{z}_k, \beta_a, \delta_a, \hat{\mathbf{x}}_k, \hat{\theta})$.

5) Process model: The state evolution of RWEPs, situations and impacts is governed by $f(\cdot)$. The state evolution of the isolated sub-world depends on previous state[2] $\mathbf{x}_{k-1}$, the previous control input $\mathbf{u}_{k-1}$, the static parameters θ of the sub-world and the uncertainties associated with the model $\mathcal{M}$. The subscripts δ_e and γ in $f_{\delta_e,\gamma}$ indicate that the model is influenced by the epistemic uncertainties in the abstraction of how RWEPs operate (δ_e), and the abstraction of isolating part of the world (γ). Whether the model explicitly considers these uncertainties is another matter. In Fig. 1, $f_{\delta_e,\gamma}$ is not shown to explicitly consider them, since most typical systems do not; however in a complete model, they should be considered. Most models typically take aleatoric uncertainty δ_a (randomness or noise) in the state evolution equation $f(\cdot)$, and hence $f_{\delta_e,\gamma}$ is a function of δ_a.

In most typical fusion systems, objects (RWEPs), situations and impacts are modelled and processed separately. The inferences from object assessment typically feed into situation assessment and, in turn, the inferences from situation assessment feed into impact assessment. Here all the dynamical models upon which inferences are performed are grouped together into a joint dynamical model $f(\cdot)$. This reflects the ideal situation where inferences of objects, situations and impacts should be performed jointly (see [23] for a related concept).

6) Data/measurement/observation model: The measurement or observation model is represented by $g(\cdot)$, where $\mathbf{z}_k$ denotes the collection of observations and measurements at time k. In most cases the measurement independence assumption holds, meaning that the measurement is conditioned only on the current state $\mathbf{x}_k$ (for example a probabilistic data model utilising a distribution $p(\mathbf{z}_k|\mathbf{x}_k)$), but can be generalised if that is not the case. Furthermore, $\mathbf{z}_k$ depends on the collection of sensor controls $\mathbf{s}_k$. As with the process model, the function $g_{\alpha,\beta_e,\gamma}$ is characterised by the uncertainty associated with the representation of the data (α), the generation of data (β_e), and the isolation of the sub-world (γ). Again, these may or may not be explicitly captured by the data model $g(\cdot)$. As with the process model, aleatoric measurement uncertainty β_a (for example measurement noise) typically does form part of $g(\cdot)$, and as such, $g_{\alpha,\beta_e,\gamma}(\cdot)$ is a function of β_a.

The overarching model $\mathcal{M}$ can represent models used within the fusion engine on multiple scales, since the above taxonomy can apply to RWEPs (objects), groups of RWEPs (situations) or models of how RWEPs can be influenced by control inputs (impacts).

7) Inference: The objective of having models as proxies for reality, is for the purpose of making inferences about reality, and in this case about the isolated sub-world of interest. Since the states $\mathbf{x}_k$ and parameters θ are hidden, the model provides equations for relating the observations to parameters as well as current and past states. The inference algorithm is tightly coupled with how uncertainty is represented within the fusion system. The combination operation inherent in fusion is implicitly contained in the functions ξ and ρ, as these functions have $\mathbf{z}_k$ as an input. The symbols $\hat{\mathbf{x}}_k$ and $\hat{\theta}$ denote the state and parameter inferences respectively. These are distinct from $\mathbf{x}_k$ and θ, since the inference process may not be exact. In the probabilistic case, the outputs of the fusion system are probability distributions, meaning that $\mathcal{U}$ takes the form of a joint probability distribution over system inputs $\mathbf{z}_k$ and outputs $\hat{\mathbf{x}_k}$, $\hat{\theta}$, i.e. $\mathcal{U}(\hat{\mathbf{x}}_k, \hat{\theta}, \mathbf{z}_k)$. This corresponds to the joint uncertainty supports between different inputs, different outputs, and also between inputs and outputs as in [24]. The model $\mathcal{M}$ and the inference process $\mathcal{I}$ together form ADP-3, the *reasoning* and *combined information* parts of the atomic decision process.

[2] This is the first order Markov principle for a dynamical model, and this view can easily be extended to higher order Markov chains if necessary

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C. Decide

The outputs of the inference engine at time k are the inferences about RWEPs, situations and impacts and their uncertainties, and are represented by $\tilde{\mathbf{y}}_k$. This quantity is fed into the decision scheme $\mathcal{D}$. In a system where the uncertainty representation is frequentist (non-Bayesian) statistics, the decision $\mathbf{d}_k$ thresholds some uncertainty support to end up with a non-probabilistic estimate of the world states and/or parameters. In that case, the output of such a process is a decision denoted by $\mathbf{d}_k$. In the case of using Bayes risk for decisions, the decision scheme and resource management blocks combine, since $\mathbf{s}_k$ and $\mathbf{u}_k$ are optimised directly such that a utility function is optimised. The decision scheme is then concerned with balancing the reward/cost of events with the probability of them occurring, for example by maximising the expected reward (or minimising the expected cost). The decision scheme and its output correspond to ADP-4 in the atomic decision process. The model $\mathcal{M}$ will be used to make predictions under different actions $\mathbf{s}_k$ and $\mathbf{u}_k$ with the inferred $\hat{\mathbf{x}_k}$, $\hat{\theta}$ in order to optimise the decision and maximise some utility/reward, or minimise some cost/loss function.

D. Act

The resource management block then calculates the necessary sensor controls $\mathbf{s}_k$ and sub-world controls $\mathbf{u}_k$ that will be required to execute the decision $\mathbf{d}_k$. It should be noted that although the information fusion system (including the sensors) is explicitly indicated in Fig. 1 as being separate from the real world, this is not actually the case. In a real setting, the fusion system is very much part of the real world. However, it is assumed that the only effect the fusion system has on the real world is through the quantities $\mathbf{s}_k$ and $\mathbf{u}_k$, and that all other effects are deemed to be negligible. Whether this is actually the case depends on the accuracy of the understanding of the effect of $\mathbf{s}_k$ and $\mathbf{u}_k$ on the real world in the model $\mathcal{M}$ and in the decision scheme $\mathcal{D}$.

TABLE II: Table of symbols together with examples from multi-sensor multi-target tracking with track fusion use case

Symbol	Example
RWEP	An aircraft that can be sensed by radars
Isolated sub-world	Area that is within range of radar network
$D_{i,k}$	All EM returns at time k from targets sensed by radar i
Sensor i	The ith radar in a network of air surveillance radars
$\Omega_{n,k}$	Dynamical characteristics (mass, powerplant, airfoil etc.) of the nth aircraft
ω_i	Dynamical characteristics (mass, powerplant, airfoil etc.) of all aircraft, as well as dynamical characteristics owing to interactions between aircraft, all observed by sensor i
z_i	All radar tracks at time k from radar i
$\mathcal{Z}_i$	Bayesian probability (sensors), Fuzzy natural language (HUMINT)
$h_i(\cdot)$	Probability density function of filtering densities parameterised by means and covariances
$\mathbf{x}_k$	Combined state of all targets after track fusion
$\mathbf{z}_k$	Combined state vectors of all tracks before fusion
$f_{\delta_e,\gamma}(\cdot)$	Almost constant velocity dynamical model
$g_{\alpha,\beta_e,\gamma}(\cdot)$	Gaussian filtering probability densities for radar tracks
ρ	N/A, since $\mathcal{Z}$ and $\mathcal{UR}$ are both probabilistic
$\mathbf{u}_k$	Message to fighter to intercept target
$\mathbf{s}_k$	Message to increase scan rate of a radar
θ	New track density
α	Uncertainty associated with quantisation error in radar digital to analog converter
β_e	Uncertainy owing to Gaussian approximation of measurement noise in rectangular coordinates
β_a	Measurement noise
δ_e	Uncertainy owing to Gaussian approximation of plant noise to represent target manoeuvres
δ_a	Plant noise
γ	Uncertainty owing to ignoring targets out of range of the radar network
$\mathcal{UR}$	Bayesian probabilistic representation
$\mathcal{U}$	Probability distribution
$\hat{\theta}$	Inferred new track density
$\hat{\mathbf{x}}_k$	Inferred distribution of the states of all targets after fusion
$\nu(\cdot)$	N/A - Bayes risk used, therefore $\nu(\cdot)$ not required
$\phi(\cdot)$	A function which finds the set of controls $\mathbf{s}_k$ which minimises the sum of posterior covariances of all targets
$\chi(\cdot)$	A function which finds the set of controls $\mathbf{u}_k$ which minimises the threats to defended assets

III. Example Use Cases

Two example use cases demonstrating the fusion uncertainty evaluation taxonomy are presented here. The first involves a multi-sensor multi-target tracking system with a network of radars and a central track fusion functionality. The second involves an anti-rhino poaching decision support information fusion system.

A. Multi-target multi-sensor tracking

Table II contains a list of the variables of the taxonomy presented in this use case. Since most of the detail of the mapping between Fig. 1 and the use case is contained in the table, only a brief description of the use case is provided here in the text. Also, the information fusion community is quite familiar with the multi-sensor multi-target tracking problem.

Along the lines of the OODA loop, RWEPs represent aircaft that can be sensed by a network of radars (for example as in [25] and [26]). The radars are intelligent sensors, in that they already provide processed (filtered) information to the fusion system in the form of target tracks and filtering covariances. This is opposed to centralised measurement fusion [17], where the radar sensors provide measurements and measurement covariances. As such the fusion engine combines the tracks from several radars to result in one fused track for each target, all contained within the joint inferred state vector $\hat{\mathbf{x}}_k$. This vector and its associated uncertainty support is used in the decision scheme and resource management functional blocks to a) direct the radars through $\mathbf{s}_k$ to minimise (for example) the sum of covariances of all tracks and b) to decide and communicate through $\mathbf{u}_k$ whether to scramble fighters to intercept targets deemed to be serious threats based on some cost/benefit analysis.

B. Counter rhino poaching decision support

The rhino poaching use case involves a decision support system that directs attention of the rangers to the areas with

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TABLE III: Table of symbols together with examples from rhino anti-poaching fusion system use case

Symbol	Example
RWEP	Moving rhinos, poachers and rangers in a national park.
Isolated sub-world	National park partitioned into 1 sq. km. cells $A_j, j = 1, \ldots, N$
$D_{i,k}$	Poacher tracks in the sand, body heat, magnetic fields generated by rifles, rain
Sensor i	Ranger, infrared camera or magnetic sensor, weather station some distance away, GPS rhino collar
$\Omega_{n,k}$	Behavioural characteristics of rhinos, poachers and rangers
ω_i	All behavioural characteristics of all rhinos, rangers and poachers within range of sensor i
z_i	Binary random variables representing the ranger HUMINT reports, infrared binary detection probabilities, magnetic sensor detection probabilities or binary variable denoting the probability of rain at that location, noisy Latitude and Longitude
$\mathcal{Z}_i$	Bayesian probabilities.
$h_i(\cdot)$	Discrete probability distributions.
$\mathbf{x}_k$	The set of all hidden variables, such as the binary variables representing a poaching event in A_j, the presence of poachers and the presence of rhinos, respectively.
$\mathbf{z}_k$	The set of all observed variables (evidence), such as HUMINT reports, sensor inputs and all the context data.
$f_{\delta_e,\gamma}(\cdot)$	Equations predicting the motion of poachers and possibly rhinos
$g_{\alpha,\beta_e,\gamma}(\cdot)$	Data/measurement/ models for HUMINT reports, and sensors
ρ	Uncertainty related to converting a natural language statement (HUMINT) to a binary probabilistic representation, i.e. $\mathcal{Z}$ is a vague language statement and $\mathcal{UR}$ is Bayesian probabilistic
$\mathbf{u}_k$	Orders to the ranger troops
$\mathbf{s}_k$	Commands to the sensory systems, such as directing a drone with sensors (e.g. cams) or rangers to a specific area.
θ	Bayesian network conditional probability tables
α	Uncertainty associated with qualitisation error of human natural language understanding
β_e	The uncertainty associated with possibly incorrect conditional probabilities relating the observable variables with the rest of the Bayesian network
β_a	The uncertainties that are *modelled by* conditional probabilities.
δ_e	Uncertainties regarding the causal relations/correlations between the modelled variables and the correctness of their CPTs
δ_a	Uncertainties *modelled* by the hidden variables (for example poacher present) of the model
γ	Uncertainty associated with ignoring events from neighboring private game reserves
$\mathcal{UR}$	Bayesian probabilistic representation
$\mathcal{U}$	Discrete probability distribution
$\hat{\theta}$	Simply the joint output variables of the junction tree algorithms, whereas $\mathcal{U}(\hat{\theta})$ is the joint posterior.
$\hat{\mathbf{x}}_k$	N/A, since there are no time varying models in this example
$\nu(\cdot)$	Decision that poacher is assumed to be in a cell
$\phi(\cdot)$	Optimisation algorithm for deciding which ranger to use and determining the route for chosen rangers
$\chi(\cdot)$	Optimisation algorithm determining the best tasking of the existing mobile sensors in the field

elevated risk of poaching. The system outputs a probability heat map [27], [28] that indicates the suitability for poaching at a specific point in space and time. Given such information, the rangers can position scarce resources such that the chance of poaching prevention is improved. Thus, the decision support system for counter rhino poaching operations covers all of the components of the OODA loop. Additionally, there are human intelligence (HUMINT) reports of the field operations as well as the current status of the international rhino trafficking agencies.

Figure 2 illustrates a very simple OODA loop for the counter rhino poaching system. In the first iteration (Figure 2b), an observation is made in cell (1,1) (**Observe**). It is a false detection, though, as the poacher is in cell (1,2). The model (probability map in this case) is inferred from the observation (**Orient**). From the model, the decision is made that cell (1,1) is the target cell (**Decide**). Based on resource availability, a ranger is sent to cell (1,1) (**Act**). In Figure 2b the ranger observes that the poacher is *not* present in cell (1,1) and this is the new observation (**Observe**). Based on this observation the model is updated (**Orient**) and cell (1,2) is chosen as the target cell (**Decide**). The ranger moves to cell (1,2)(**Act**). Unfortunately the rhino was already poached and the poacher is moving on to cell (2,2).

As in [27], the central part of the overall system is a set of Bayesian threat models, each with context evidence instantiated to correspond to a specific area or cell A_k. A threat model is implemented as a Bayesian Network (BN) that captures the correlations between various context factors influencing the poaching (facilitators/inhibitors) as well as observable phenomena that might indicate an imminent threat. The strengths of causal relationships between variables are captured by conditional probability tables (CPTs). The Bayesian network then fixes the evidence of the context variables for a specific A_j, ignoring the same phenomena from a neighboring location. As such, not all context is represented either due to lack of knowledge or for the sake of simplicity. Such missing phenomena become confounders and is captured by the isolation uncertainty variable γ. The outputs of such Bayesian threat models are represented as colour gradients on a discrete probability heat map. The modelling is characterised through a great variety of variables, as very heterogeneous phenomena are correlated.

Dependent on the current knowledge of the situation and the associated uncertainties captured by the outputs of the fusion system, one could compute the positions for the drones and the mobile observers, such that the expected reduction of the uncertainty would be minimised, while the physical constraints of the mobile sources would be considered (e.g. the speed and range of a mobile platform). The external and internal processes can be managed with the measures of effectiveness and measures of performance respectively [29].

IV. Evaluation under the URREF

As the main purpose of this paper is to make the uncertainty subjects of evaluation in a fusion system explicit, evaluation

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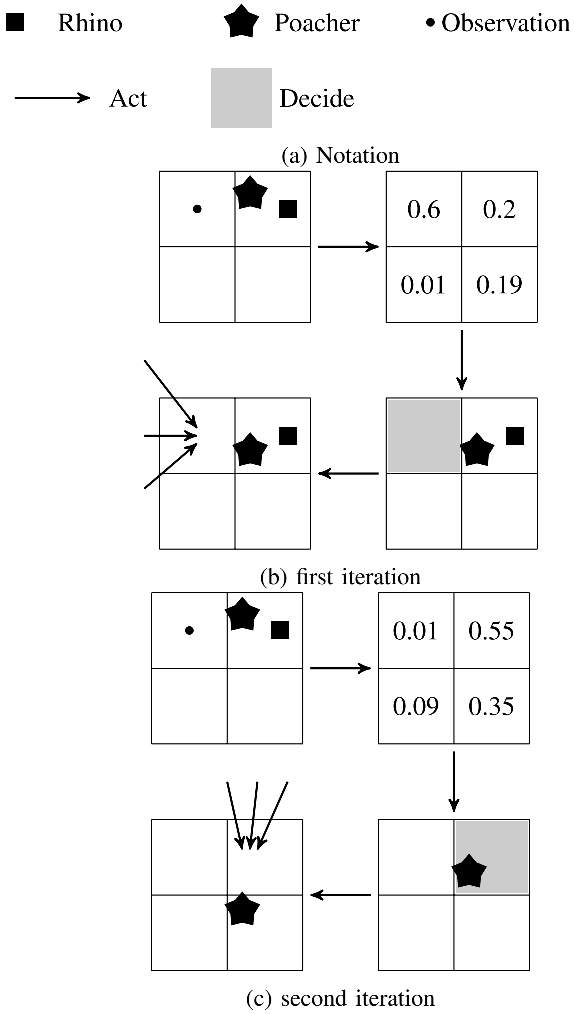

Fig. 2: Counter rhino poaching - OODA loop illustration

under the URREF will only be briefly discussed here. A more in depth and complete treatise of the evaluation of uncertain variables, representations and supports in Table I is reserved for future work. As such, an objective of this paper is to clarify *EvaluationSubject* in the URREF ontology.

A. ADP-1

Sensors (humans and technological sensors) can be evaluated using the *DataHandlingCriteria* consisting of *Traceability* and *Interpretation* as well the *DataCriteria* consisting of *Credibility* (*Objectivity*, *ObservationalSensitivity*, *SelfConfidence*), *Quality* (*Veracity*, *Accuracy*, *Precision*), *RelevanceToProblem* and *WeightOfEvidence*. The class *UncertainEvidence* and its components can be used to further characterise the information entering the fuson system.

B. ADP-2

Most of the epistemic uncertainties in the model $\mathcal{M}$ can be evaluated according to *RepresentationCriteria* which consists of *KnowledgeHandling*, *Simplicity*, *Expressiveness*, *Adaptability* and *Compatibility*. This is closely related to *UncertaintyType*, and whether a particular type of uncertainty is adequately captured by the fusion engine uncertainty representation $\mathcal{UR}$. Hence the uncertainty variables $\rho, \alpha, \beta_e, \delta_e$ and γ can be evaluated according to *RepresentationCriteria*.

C. ADP-3

The inference engine $\mathcal{I}$ can be evaluated by using *ReasoningCriteria*, which consists of *ComputationalCost*, *Scalability*, *Performance* and *Consistency*. The output of the inference engine can again be evaluated according to the *DataCriteria*, as with the input of the fusion engine. Notably, the output of a fusion process may form the input of another fusion process in the case of distributed fusion.

D. ADP-4 and Resource Management

The uncertainty about the effect of actions $\mathbf{s}_k$ and $\mathbf{u}_k$ on the real world in the model $\mathcal{M}$, reduces the optimality of the decision process. This is again a type of epistemic uncertainty that may be evaluated according to *RepresentationCriteria*. Furthermore, the decision process is a form of reasoning (through optimisation), and can be therefore be evaluated according to *ReasoningCriteria*. Maximising the expected utility combines uncertainty with utility, and the utility part carries an element of subjectivity related to a desired outcome. In many cases a desired outcome is the combination of conflicting and competing objectives with relative weigtings. As such some *DataCriteria* such as *Objectivity*, *RelevanceToProblem* and *WeightOfEvidence* may be relevant.

V. Conclusion

This paper considers the flow of information in the atomic decision process, in order to clarify and explicitly state what the subjects of evaluation in an information fusion system are. It is possible to trace the addition of uncertainties, by going through the process of noting all the places where uncertainties enter the information fusion process, and more holistically, the decision process. In [9], uncertainties were considered that enter during the design phase of a fusion system, and also noted recent advances in the field of uncertainty quantification. Here, those uncertainties are considered together with uncertainties that enter at runtime.

Two use cases (one well known, and another less well known) illustrate how the uncertain quantities and their associated uncertainty supports (collectively uncertainty representations) can be mapped to simplified versions of real example problems. Conceptually, the taxonomy presented allows for scaling to more complex fusion problems, but if all possible uncertainties are considered and accounted for in a typical fusion system, the resulting analysis may be daunting. As such the benefits of having such a complete uncertainty quantification of a fusion system need to be evaluated, since some of the uncertainties introduced may have a negligible effect on system performance. However, one will have to go through a process of sensitivity analysis to see which types of uncertainties can be safely ignored during design and runtime.

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