A Unification of Sensor and Higher-Level Fusion

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Abstract – A State Transition Data Fusion Model is introduced as an extension of the dominant sensor fusion paradigm to provide a unification of both sensor and higher-level fusion.

Keywords: Sensor Fusion, Higher-Level Fusion, Data Fusion, JDL Model, Object Assessment, Situation Assessment, Impact Assessment.

1 Introduction

In [1] and [2] data fusion is characterised broadly by the author as “the process of utilising one or more data sources over time to assemble a representation of aspects of interest in an environment”. The traditional roots of the data fusion community are in sensor fusion, where the “data sources” are established sensors and the “aspects of interest in the environment” are moving objects, each typically represented by a set of state vectors. But demands on the data fusion community are beginning to exceed this narrow intent.

In the national security context, the threat of terrorism ([3]) and the impetus of network centric warfare (NCW) ([4]) are expanding the “aspects of interest in the environment” beyond military target tracking considerations to include issues pertaining to: biography, economy, society, transport and telecommunications, geography, and politics, in addition to combinations of the aforementioned. Commensurately, the “data sources” are beginning to exceed military sensor systems, to include: communication systems, databases, web sites, public media, human sources, et cetera. The demand for this kind of capability is also emerging in the commercial and wider social context, as advances in transport and telecommunications foster a cascading effect across organisational structure, function, location and change ([5] section 4.1). Globalisation, decentralisation and strategic alliance are creating a need for machine based data fusion that can process more information to allow faster decisions by fewer people. The increasing demand requires our machines to extend well beyond sensor fusion into so called higher-level fusion. This paper seeks to extend the dominant sensor fusion paradigm to provide a unified framework that applies to both sensor and higher-level fusion. It provides a means of stating the data fusion problem generally.

2 The Deconstructed JDL Model

The Joint Directors of Laboratories (JDL) model remains the most dominant model of data fusion. Figure 1 illustrates its revised form ([6]).

Figure 1. The JDL Data Fusion Model

The JDL model has the benefit of incorporating both sensor and higher-level fusion, with the product of sensor fusion taken to include sub-object assessments, object assessments, and their refinement; while the product of higher-level fusion is taken to comprise situation assessments, impact assessments and their refinement.

Figure 2. The Deconstructed JDL Data Fusion Model

Figure 2 exposes the resultant deconstructed JDL model, where:
- object assessments are stored representations of objects;
- situation assessments are stored representations of relations between objects; and
- impact assessments are stored representations of effects of relations between objects.
Both the JDL model and its deconstructed form, segregate object, situation and impact fusion into amorphous blocks, without explaining their internal mechanisms. In doing so those models celebrate the difference between object, situation and impact fusion, but at the expense of demonstrating their unity. Similarly, in [7] the author notes that sensor fusion representations of the world fail to scale up to higher-level fusion. A situation assessment of a missile targeting a communications tower will more likely resemble \{missile(x56), targeting(x56,x7), comms_tower(x7)\} than a set of state vectors like \(<id,t,x,\frac{dx}{dt},y,\frac{dy}{dt},\theta,\frac{d\theta}{dt},...>\). Nonetheless, there is a unifying framework for data fusion which the State Transition Data Fusion (STDF) Model introduced in this paper aims to expose.

### 3 The STDF Model

Under the STDF model, parts of the world are understood in terms of states and transitions between those states. At any time \(k\), the world is composed of a number of states, including \(s(k)\), and up to time \(k\) the world is understood in terms of sets of transited states, including \(\{s(t) \mid t \in \text{Time} \& t \leq k\}\). At time \(k+1\) the machine senses new states of the world, including \(s(k+1)\), through its sensors and transfers the sensed data to an observation process.

The observation process draws upon a prediction process, which accesses previous representations of states of the world to identify predicted observations under previous explanations. On the basis of comparisons between actual and predicted observations, control transfers to an explanation process that establishes new representations about states of the world. Under this framework, data fusion concerns the prediction, observation and explanation of state transitions in the world. The process: observes to explain; explains to predict; and predicts to observe. As science itself is often cast in terms of prediction and explanation through observation of the world, the STDF framework underscores the fundamental nature, and hence broad applicability, of data fusion.

Figure 3 illustrates a more detailed account of the STDF model.

- At time \(k+1\) the machine senses a state \(s(k+1)\) of the world through its sensors and transfers its sensed data \(e(k+1)\) to an observation process.
- The observation process involves a detection process to identify a detection \(d(k+1)\); a registration process that normalises the detection relative to a frame of reference, to yield an observation \(o(k+1)\); and then an association process.
- The association process first draws upon a prediction process, which: accesses previous representations \(\hat{s}(k|k)\) of states of the world at time \(k\); uses a state prediction process to posit predicted states \(\hat{s}(k+1|k)\); and then applies these to an observation prediction process to posit predicted observations \(\hat{o}(k+1|k)\).
- The association process matches observations to (zero, one or more) predicted observations and then transfers control to an explanation process. If the observation \(o(k+1)\) is matched to a predicted observation \(\hat{o}(k+1|k)\), then an update process updates the representation of the state with the explained state \(\hat{s}(k+1|k+1)\). If the observation \(o(k+1)\) is valued and fails to match a predicted observation \(\hat{o}(k+1|k)\), then an initiation process can insert a representation of a new state with state information \(\hat{s}(k+1|k+1)\).
Figure 4. The STDF Model for Object Assessments

Through a data fusion process involving prediction, observation and explanation, related states of the world \( \{ s(t) \mid t \in \text{Time} \& \ t \leq k \} \) come to be represented in the machine as a set of explained states \( \{ \hat{s}(t) \mid t \in \text{Time} \& \ t \leq k \} \). The bidirectional arrow labeled “external interactions” in Figure 3 is used to signify distributed data fusion, by expressing scope for interactions with other data fusion systems. The bidirectional arrow is deliberately non-specific about the nature of external interactions. It could include access to or insertion of information across data fusion systems, or the interaction through any of the prediction, observation or explanation processes in different data fusion systems. Issues relating to distributed data fusion are raised in [5].

4 STDF for Object Assessments

Object assessments present an understanding of the world in terms of objects with measurable properties. Consequently, object assessments are primarily numerically based. Changes in the measurable properties over time are taken to reflect objects as transitions in object instances over time. Within the STDF model, an object instance at time \( k \) is a state of the world \( s(k) \) understood as a state vector \( \mathbf{u}(k) \) of measured values. An object \( \{ s(t) \mid t \in \text{Time} \& \ t \leq k \} \) at time \( k \) is understood as a set of transitioning object instances and so each object at time \( k \) is understood as a set of state vectors \( \mathbf{u}(k) = \{ \mathbf{u}(t) \mid t \in \text{Time} \& \ t \leq k \} \). Through a data fusion process involving prediction, observation and explanation, the state vector \( s(k) \) as \( \mathbf{u}(k) \) comes to be represented as the estimate \( \hat{u}(k) \), while object \( \{ s(t) \mid t \in \text{Time} \& \ t \leq k \} \) as \( \mathbf{u}(k) = \{ \mathbf{u}(t) \mid t \in \text{Time} \& \ t \leq k \} \) at time \( k \) comes to be represented as a set of state estimates \( \hat{u}(k) = \{ \hat{u}(t) \mid t \in \text{Time} \& \ t \leq k \} \).

Sensor fusion comprises the sub-object assessment and object assessment portions of the JDL model. In the STDF model for object assessments, the signal processing
process delivers JDL sub-object assessments while the coordinate registration, data association, state prediction, measurement prediction, update state estimate and initiate state estimate processes provide JDL object assessments.

5 STDF for Situation Assessments

Situation assessments present an understanding of the world in terms of situations expressed as sets of sets of statements about the world. Consequently, situation assessments are primarily symbolically based. Changes in the statements over time are taken to reflect situations as transitions in situation instances over time. Within the STDF model, a situation instance at time k is a state of the world s(k) understood as a state of affairs \( \Sigma(k) \), comprising a set of statements about the world in some formal language. A situation \( \{s(t) \mid t \in \text{Time} \& t \leq k\} \) at time k is understood as a set of transitioning situation instances and so each situation at time k is understood as a set of states of affairs \( \Sigma(k) = \{\Sigma(t) \mid t \in \text{Time} \& t \leq k\} \).

Through a data fusion process involving prediction, observation and explanation, the state of affairs s(k) as \( \Sigma(k) \) comes to be represented as the explained set \( \hat{\Sigma}(k) \), while situation \( \{s(t) \mid t \in \text{Time} \& t \leq k\} \) as \( \Sigma(k) = \{\Sigma(t) \mid t \in \text{Time} \& t \leq k\} \) comes to be represented as a set of explained states of affairs \( \Sigma(k) = \{\hat{\Sigma}(t) \mid t \in \text{Time} \& t \leq k\} \). \( \hat{\Sigma}(k) \) is a situation assessment composed of situation instance assessments \( \hat{\Sigma}(t|t) \) for \( t \leq k \).

Figure 5 is a situation assessment adaptation of Figure 3.

- At time \( k+1 \) the machine senses a state \( s(k+1) \) of the world, understood as a state of affairs \( \Sigma(k+1) \), through its sensors and transfers its sensed data \( e(k+1) \) to an observation process.

- The observation process involves the object assessment process outlined in section 4 to identify an object instance assessment (state estimate) \( \hat{u}(k+1|k+1) \); a semantic registration process that normalises the object assessment relative to a semantic frame of reference, to yield an observed propositional statement \( \Phi(k+1) \) about the world; and then a proposition association process.

- The proposition association process first draws upon a prediction process, which: has accessed previous representations \( \hat{\Sigma}(k) \) of a state of affairs at time k; used an impact assessment process to posit predicted states of affairs \( \hat{\Sigma}(k+j|k) \); and then applied these to a set expectation process that stores expected and anticipated propositions \( \hat{\Phi}(k+j) \).

- The proposition association process transfers control to an explanation process. If the observed propositional cue \( \Phi(k+1) \) matches (one or more) expected propositions \( \hat{\Phi}(k+1|k) \), then control resumes with an update situation assessment process that updates the representation of the situation with the explained state of affairs \( \hat{\Sigma}(k+1|k) \). If the observed proposition \( \Phi(k+1) \) matches an anticipated proposition \( \hat{\Phi}(k+1|k) \), then control transfers to an initiate situation assessment process that inserts a representation of a new situation with state of affairs \( \tilde{\Sigma}(k+1|k+1) \). Completion of the explanation process for time \( k+1 \) can trigger the prediction process for time \( k+1 \).

Higher-level fusion comprises the situation assessment and impact assessment portions of the JDL model. In the STDF model for situation assessments, the object assessment process delivers sensor fusion; the semantic registration, proposition association, update situation assessment and initiate situation assessment processes provide JDL situation assessments; and the impact
assessment and set expectations processes facilitate JDL impact assessments.

For Kalman filter based object fusion, state vector transitions are represented by $y(k+1) = F(k+1) y(k) + u(k+1)$, for: behavioural model $F(k+1)$ expressed as an $n \times n$ state transition matrix; known deterministic n-dimensional input vector $g(k+1)$; and $y(k+1)$ as an n-dimensional zero mean, white, Gaussian noise vector, while each m-dimensional observation vector has $H(k+1) y(k) + v(k+1)$, for: m:n measurement matrix $H(k+1)$ and m-dimensional zero mean, white, Gaussian noise vector $v(k+1)$. For situation fusion, let $W(k)$ be a probability space in which: $W$ is the sample space of all possible worlds for atomic formulae $\{ \alpha \mid \text{atomic(}\alpha)\}$, represented by $W = \{(\alpha \mid \alpha \in A) \cup \{\neg \alpha \mid \alpha \in A\} \mid A \in P(\alpha \mid \text{atomic(}\alpha))$ for powerset $P(\alpha \mid \text{atomic(}\alpha))$. For each k, let random variable $W(k)$ in $W \rightarrow \{0, 1\}$ identify a proposition. The state of affairs $\Sigma(k)$ at time k corresponds to an event in $E$ and so $p(\Sigma(k)) = \sum_{W(k) \in \Sigma(k)} p(W(k))$. Similarly, let random variable $\Phi(k) : E \rightarrow \{0, 1\}$ identify an observation from the sample space $E$ at time k. State of affairs transitions are assumed Markovian, i.e. $p(\Sigma(k+1) \mid W(k)) = p(W(k) \mid \Sigma(k))$, and observations are assumed conditionally independent i.e. $p(\Phi(k) \mid W(k)) = \prod_{W(k) \in \Sigma(k)} p(\Phi(k) \mid W(k))$.

The state of affairs counterpart to state vector $y(k+1)$ is $\Sigma(k+1) \subseteq \{ \sigma \mid \Sigma(k) \cup \Delta(k+1) \cup \Pi(k+1) \subseteq \hat{\Sigma}(k+1) \} \subseteq \{ \sigma \mid \Sigma(k) \cup \Delta(k+1) \cup \Pi(k+1) \subseteq \hat{\Sigma}(k+1) \}$ for: behavioural model $F(k+1)$ expressed as a semantic formal theory (f8); known input change expressed through a probability space in which:

- $\Delta(k+1)$ is given by $p(\Delta(k+1) \mid \Sigma(k)) = \sum_{\sigma \in \Sigma(k)} p(\Delta(k+1) \mid \sigma) p(\sigma \mid W(k))$.
- $\Pi(k+1)$ is given by $p(\Pi(k+1) \mid \Sigma(k)) = \sum_{\sigma \in \Sigma(k)} p(\Pi(k+1) \mid \sigma) p(\sigma \mid W(k))$.

If the observation $\hat{\sigma} = \sigma$ is matched to a predicted state of affairs $\hat{\Sigma}(k+1)$, then an update situation assessment $\tilde{\sigma} = \hat{\sigma}$ of possible state of affairs $\Sigma(k+1)$, given past observations $\{\Phi(1), ..., \Phi(k)\}$, is given by $p(\sigma \mid W(k)) = \prod_{W(k) \in \Sigma(k)} p(\Phi(k) \mid W(k))$.

Numerical computing with observations has then migrated to symbolic reasoning based in observation.

To predict $\Phi(k+1)$, the situation fusion counterpart to n-dimensional state prediction vector $\hat{y}(k+1) = F(k+1) y(k) + g(k+1)$ is predicted state of affairs transition $\hat{\Sigma}(k+1)$, where $\Sigma(k+1) \subseteq \{ \sigma \mid \hat{\Sigma}(k+1) \}$ for: known input change expressed through a probability space in which:

- $\Delta(k+1)$ is given by $p(\Delta(k+1) \mid \Sigma(k)) = \sum_{\sigma \in \Sigma(k)} p(\Delta(k+1) \mid \sigma) p(\sigma \mid W(k))$.
- $\Pi(k+1)$ is given by $p(\Pi(k+1) \mid \Sigma(k)) = \sum_{\sigma \in \Sigma(k)} p(\Pi(k+1) \mid \sigma) p(\sigma \mid W(k))$.

This requires the predicted observation $\hat{\Phi}(k+1)$ to be a semantic consequence of the predicted state $\hat{\Sigma}(k+1)$ relative to the semantic observation model $H(k+1)$. The uncertainty associated with observations is determined by $p(\Phi(k+1) \mid W(k+1)) = \sum_{W(k+1) \in \Sigma(k+1)} p(\Phi(k+1) \mid W(k+1))$ with $p(\Phi(k+1) \mid W(k+1))$ obtained by probabilistic inference from $H(k+1)$ and $\Delta(k+1)$, and with $p(\Phi(k+1) \mid W(k+1))$ obtained by inductive explanation. $\hat{\Phi}(k+1)$ can be chosen as the most probable $\hat{\Sigma}(k+1)$ given past observations $\{\Phi(1), ..., \Phi(k)\}$. The counterpart to the object observation prediction $\hat{\delta}(k+1) = H(k+1) y(k+1) + v(k+1)$ is $\phi(k+1) = \sum_{\delta(k+1) \in \delta(k+1)} p(\delta(k+1) \mid \sigma)$.

If the observation $\hat{\sigma}$ is matched to a predicted observation $\hat{\Phi}(k+1)$, then an update situation assessment process updates the representation of the object with the situation assessment $\hat{\Sigma}(k+1)$. To update the assessment $\Sigma(k+1)$ associated with the
observation \( \Phi(k+1) \), a Bayesian approach is obtained through
\[
p(\Sigma(k+1)|\{\Phi(1), \ldots, \Phi(k+1)\}) = \sum_{\omega \in W} p(W(k+1)|\omega) \cdot p(\omega|\Phi(1), \ldots, \Phi(k))
\]
If the observation \( \Phi(k+1) \) fails to match a predicted observation \( \hat{\Phi}(k+1|k) \), but is anticipated, then an initiate situation assessment process can also insert a representation of a new object with state estimate \( \Sigma(k+1|k+1) \).

6 STDF for Impact Assessments

Impact assessments present an understanding of the world in terms of scenarios expressed as sets of situations. Consequently, impact assessments are primarily symbolically based. Changes in the statements over time are taken to reflect scenarios as transitions in scenario instances over time. Within the STDF model, a scenario instance at time \( k \) is a state of the world \( s(k) \) understood as a scenario state \( S(k) = \Sigma(\partial(k)) = \{\Sigma(n) | n \in \text{Time} \& n \leq \partial(k)\} \), for monotonic look ahead time \( \partial(k) \geq k \).

Consequently, \( S(k) = \{\Sigma(n) | n \in \text{Time} \& n \leq k\} \cup \{\Sigma(n) | n \in \text{Time} \& k < n \leq \partial(k)\} \) is composed of situation \( \Sigma(k) = \{\Sigma(n) | n \in \text{Time} \& n \leq k\} \) and partial future \( \Sigma(n) | n \in \text{Time} \& k < n \leq \partial(k)\). A scenario \( \{s(t) | t \in \text{Time} \& t \leq k\} \) at time \( k \) is understood as a set of transitioning scenario instances and so each scenario at time \( k \) is understood as the set of scenario states \( S(k) = \{\Sigma(t) | t \in \text{Time} \& t \leq k\} \).

A world scenario \( S(k) \) at time \( k \) is a monotonically increasing set of scenario states (situations) in the sense that if \( t_1, t_2 \in \text{Time} \) and \( t_1 < t_2 \leq k \), then \( S(t_1) \subseteq S(k) \), \( S(t_2) \subseteq S(k) \) and \( S(t_2) \subseteq S(t_1) \).

Through a data fusion process involving prediction, observation and explanation, the scenario state \( s(k) \) as \( S(k) \) comes to be

\[ \text{Monotonicity requiring that } \partial(k_2) \geq \partial(k_1) \text{ whenever } k_2 > k_1. \]
represented as the explained set $\hat{S}(k) = \{\hat{\Sigma}(t|k) \mid t \in \text{Time} \& t \leq \hat{\partial}(k)\}$, while the scenario $\{s(t) \mid t \in \text{Time} \& t < k\}$ as $\Sigma(k) = \{\Sigma(t) \mid t \in \text{Time} \& t \leq k\} = \{\Sigma(n) \mid n \in \text{Time} \& n \leq \partial(t)\} \mid t \in \text{Time} \& t \leq k\}$ comes to be represented as a set of explained states of affairs $\hat{S}(k) = \{\hat{\Sigma}(n|t) \mid n \in \text{Time} \& n \leq \partial(t)\} \mid t \in \text{Time} \& t \leq k\}$. $\hat{S}(k)$ is an impact assessment composed of scenario instance assessments $\hat{S}(k) = \{\hat{\Sigma}(n|t) \mid n \in \text{Time} \& n \leq \partial(t)\}$ for $t \leq k$.

Figure 6 is an impact assessment adaptation of Figure 3.  
- At time $k+1$ the machine senses a state $s(k+1)$ of the world, understood as a state of affairs $\Sigma(k+1)$, through its sensors and transfers its sensed data $e(k+1)$ to an observation process.
- The observation process involves the object assessment process outlined in section 4 to identify an object instance assessment (state estimate) $\hat{\Sigma}(k+1|k+1)$; the situation assessment process outlined in section 5 to identify a situation instance assessment (state of affairs) $\hat{\Sigma}(k+1|k+1)$; and then a situation association process.
- The situation association process first draws upon a prediction process, which: has accessed previous representations $\{\hat{\Sigma}(t|k) \mid t \in \text{Time} \& t \leq k\}$ of a scenario instance at time $k$; used a predictive assessment process to posit possible courses of events $\{\hat{\Sigma}(t|k) \mid t \in \text{Time} \& k < t \leq \hat{\partial}(k)\}$ for alternative courses of action $\hat{\Sigma}$; and then applied these to a course of action assessment process that identifies the expected course of action $\hat{\xi}$ and stores its associated course of events as the future expected states of affairs $\{\hat{\Sigma}(t|k) \mid t \in \text{Time} \& k < t \leq \hat{\partial}(k)\}$, including $\hat{\Sigma}(k+1|k)$.
- The situation association process transfers control to an explanation process. If the observed state of affairs $\hat{\Sigma}(k+1|k+1)$ matches (one or more) expected state of affairs $\hat{\Sigma}(k+1|j)$ for $j \leq k$, then control resumes with an update scenario assessment process that updates the representation of the past scenario with the explained set $\{\hat{\Sigma}(t|k+1) \mid t \in \text{Time} \& t \leq k\}$. If the observed state of affairs $\hat{\Sigma}(k+1|k+1)$ fails to match an expected state of affairs $\hat{\Sigma}(k+1|j)$ for $j \leq k$, then control transfers to an initiate scenario assessment process that inserts a representation of a new scenario beginning with $\{\hat{\Sigma}(k+1|k+1)\}$. Completion of the explanation process for time $k+1$ can trigger the prediction process for time $k+1$.

Higher-level fusion comprises the situation assessment and impact assessment portions of the JDL model. In the STDF model for impact assessments, the object assessment process delivers sensor fusion; the situation assessment process provides JDL situation assessments; and the situation association, update scenario assessment, initiate scenario assessment, predictive assessment and course of action assessment processes facilitate JDL impact assessments.

Scenario prediction involves intent, capability and awareness. Concerning intent, at time $k$ each agent $A$ in the environment will harbour a number of intended effects. Each intended effect $\Psi_A(t|k)$ for $t > k$ is a future state of affairs intended for the environment at time $t$ by agent $A$ at time $k$. As a state of affairs, it is represented by a set of statements about the world. Figure 7 depicts two intended effects for agent $A$, $\Psi_A(k|k)$ and $\Psi_A(k+m|k)$ for some $m > i > k$. A set of intended effects for an agent, such as $\{\Psi_A(k+i|k), \Psi_A(k+m|k)\}$, reflects the intended transitions in intended effects over time. The set $J_A(k) = \{\Psi_A(t|k) \mid t \in \text{Time}\}$ identifies agent $A$’s course of intent (COI) at time $k$, with intended future effects $\mathcal{J}_A(k) = \{\Psi_A(t|k) \mid t \in \text{Time} \& t > k\}$ and past intentions $\mathcal{J}_A(k) = \{\Psi_A(t|k) \mid t \in \text{Time} \& t \leq k\}$. Past intentions are monotonic in that $\mathcal{J}_A(k) \subseteq \mathcal{J}_A(t)$ whenever $k < t$.

Concerning capability and awareness, at time $k$ agent $A$’s awareness of the world is represented by its current
A capability option is hereafter defined to be any activity that has the ability to transition the state of the world. Capability options can be modeled as functions by bundling together prospective concurrent actions at a given time. At time \( k \), agent A will usually have a number of capability options available to it. Performing capability option \( c_{A,1} \) alone at time \( k \) transitions the state of the world from state of affairs \( \Sigma(k) \) to state of affairs \( \Sigma(k+i) = c_{A,1}(\Sigma(k)) \). To agent A, performing capability option \( c_{A,1} \) at time \( k \) transitions its awareness \( \hat{\Sigma}_A(k|k) \) of state of affairs \( \Sigma(k) \) to its projected awareness \( \hat{\Sigma}_A(k+i|k) \) of state of affairs \( \Sigma(k+i) \). So to agent A, \( c_{A,1}(\hat{\Sigma}_A(k|k)) = \hat{\Sigma}_A(k+i|k) \). In Figure 7, agent A also considers capability option \( c_{A,2} \) at time \( k \), with \( c_{A,2}(\hat{\Sigma}_A(k|k)) = \hat{\Sigma}_A(k+2|k+i) \).

The projection process can be recursively repeated on the projected states of affairs. Capability options \( c_{A,1} \) and \( c_{A,4} \) might be considered for projected state of affairs \( \hat{\Sigma}_\hat{A}(k+i|k) \), resulting in projected states of affairs \( \hat{\Sigma}_\hat{A}(k+1|k) \). The projected state of affairs \( \hat{\Sigma}(k+i|k) \) for each sequence of capability options \( \langle c_{A,1}, \ldots, c_{A,w+1} \rangle \) is termed a course of action (COA) and the associated set \( \{ \hat{\Sigma}(t_1|k), \ldots, \hat{\Sigma}(t_w|k) \} \) of projected states of affairs termed a course of events (COE).

Of course when contemplating the effect \( \hat{\Sigma}_\hat{A}(k+i|k) \), agent A needs to not only consider the "normal effect" associated with \( c_{A,w+1} \), but also the reaction and independent actions of the environment and other agents, be they people or machines, each of whom will have their own intended effects and be contemplating courses of action to achieve them. To illustrate, in Figure 7 \( \hat{\Sigma}(t_1|k) \) begins a particular course of action to satisfy the intended course of intent \( \langle \Psi_A(k+i|k), \Psi_A(k+m|k) \rangle \) to effect an air strike on a given enemy ship, but \( \hat{\Sigma}_\hat{A}(k+i|k) \) considers an enemy course of action in which an enemy missile is launched at the aircraft to prevent that air strike, and \( \hat{\Sigma}_\hat{A}(k+i|k) \) presents the environmental impact of the missile striking the strike aircraft.

So at time \( k \), agent A performs a predictive assessment by evaluating possible \( \langle \text{COI}, \text{COA}, \text{COE} \rangle \) tuples \( \langle \langle \Psi_A(t_1|k) \mid t \in \text{Time} \land k < t \leq \hat{\sigma}(k) \rangle, \hat{\Sigma}_A(k), \langle \hat{\Sigma}_A(t_1|k) \mid t \in \text{Time} \land k < t \leq \hat{\sigma}(k) \rangle \rangle \) at time \( k \), with estimated COE \( \mathcal{E}_A(k) = \{ \hat{\Sigma}_A(t_i|k) \mid t \in \text{Time} \land k < t \leq \hat{\sigma}(k) \} \subseteq \hat{\Sigma}_A(k) \) for scenario state \( \hat{\Sigma}_A(k) \). If selected optimally, \( \mathcal{E}_A(k) \) will be the course of action that minimises the difference between the projected states of affairs and the intended effects over time. Formally this amounts to solving a dynamic programming problem, as suggested in Figure 7.

7 Conclusions

Data fusion exists as a discipline because it offers a conceptual unification of a diversity of techniques and applications. At the highest level of abstraction, “the process of utilising one or more data sources over time to assemble a representation of aspects of interest in an environment” provides a unifying theme for this diversity (section 1). At a lesser level of abstraction the JDL model (section 2) offers a greater basis for unity by identifying components of the fusion process to which the diversity of techniques and applications can be related. At a lesser level of abstraction again, the STDF model promotes an even greater basis for unity by generalizing sensor fusion to a common pattern of behaviour that applies in each of the (deconstructed) JDL components of the fusion process, without necessarily being prescriptive about the mathematical and computational techniques used to achieve that behaviour. The STDF model will hopefully engender greater commonality across the sensor fusion and higher-level fusion communities.

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References