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Information Fusion for Object & Situation Assessment in Sensor Networks★

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***Abstract*— A semantic framework for information fusion in sensor networks for object and situation assessment is proposed. The overall vision is to construct machine representations that would enable human-like perceptual understanding of observed scenes via fusion of heterogeneous sensor data. In this regard, a hierarchical framework is proposed that is based on the Data Fusion Information Group (DFIG) model. Unlike a simple *set-theoretic* information fusion methodology that leads to loss of information, *relational dependencies* are modeled as cross-machines called *relational* Probabilistic Finite State Automata using the xD-Markov machine construction. This leads to a tractable approach for modeling composite patterns as structured sets for both object and scene representation. An illustrative example demonstrates the superior capability of the proposed methodology for pattern classification in urban scenarios.**

I. Introduction

A sensor network consists of a dense collection of miniature platforms each containing sensing, communication and computing devices. Embedded in or positioned close to physical phenomenon, it can provide real-time physical data that forms the backbone of any surveillance, reconnaissance or monitoring system for military and civil operations [1]. Practical utilization of this new frontier in technology for achieving higher levels of autonomy for real-time situational awareness presents the following research challenges that need to be simultaneously addressed.

1) *Resource-constrained* nodes prohibit central data processing due to communications overheads.
2) *Limited computing power* requires efficient onboard data processing algorithms.
3) *Heterogeneous sensing* calls for a common framework for in-network information fusion.

Information dominance and real-time situational awareness are deemed critical for both military and civilian applications and have found relevance in various applications such as tactical plan recognition [2] [3], battlefield situation awareness problem [4], threat evaluation in air defense scenarios [5], and disaster response [6].

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Fig. 1. DFIG Information Fusion Model

The Data Fusion Information Group (DFIG) [7] has proposed a seven layer model for *information fusion* as shown in Figure 1. While *Data Assessment*, involves signal conditioning, transformation and signal state estimation, the objective of the *Object Assessment* layer is to estimate and predict *entity* states, such entity type, position and orientation, using data association. This is the layer where fusion of information first occurs - signal features from different sensing modalities, observing the various footprints of an *entity*, must be *fused* for estimation and prediction of the object states. This involves estimation of relationships between the footprints observed in various modalities for accurate and robust estimation of the observed *entity*. At the *Situation Assessment* layer, the objective is the estimation and prediction of the relations among entities identified at the object level for scene analysis and understanding.

Many techniques have been developed for object assessment while situation assessment is less well understood. In [8], the authors point out that situations should be modeled by some particular situation objects and some relations between these individual objects. The difficulty lies in how to properly model these relations.

The Bayesian belief network [9] [10] is one of the most popular frameworks used for situation assessment. In this framework, situations become hypotheses and objects are treated as evidences. Relations among the objects and the situations are modeled through the topology of the network

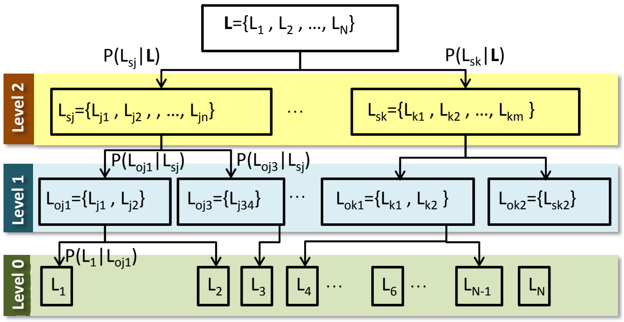

Fig. 2. A *Set-theoretic* approach to information fusion

and the conditional probabilities. A generalization of the Bayes' theory is the Dempster-Shafer theory [11]. The primary disadvantage of this kind of methods is the maintenance of the model, especially when a new situation of interest is added.

The fuzzy belief network is utilized for force aggregation and classification in situation assessment in [12]. The advantage is that the fuzzy logic is direct, intuitive and computational efficient. However, it is a heuristic approach.

An ontology-based approach is investigated in the computer science community [13]. Ontologies explicitly encode a shared understanding of some domain that can be agreed among different parties (people or computers) via a vocabulary of terms, and some specification of meaning for the terms grounded in some forms of logic [14]. However, building such an ontology model is relatively difficult for situation assessment because it is very subjective and restricted to the designers' understanding of the situation.

The knowledge based approach is mentioned in [15]. It starts with the modeling of the situation and then performs a pattern matching to identify the ongoing activity.

In this paper, we propose a data-driven approach for object and situation assessment in a semantic framework. Probabilistic finite state automata (PFSA) are used as semantic models for object assessment. Relational PFSA are constructed via the xD-Markov algorithm to capture the relational dependence among the objects at the data level. A situation is classified based on the objects and the relational PFSA. The advantage of our work is that we can obtain non-heuristic semantic models for different situations with computationally efficient algorithms. These models could be the potential inputs into higher layers of the DFIG fusion model.

This paper is organized as follows. In section II, we present our semantic framework for object assessment and situation assessment in the context of DFIG information fusion model and the xD-Markov algorithm for construction of the relational PFSA. In section III we discuss a target identification application in an urban scenario using our proposed framework to validate the theory. The paper is concluded with the recommendation for future work in Section IV.

II. The proposed architecture

A. Preliminary concepts and notations

In the formal language theory [16], an alphabet Σ is a (non-empty finite) set of symbols. A string x over Σ is a finite-length sequence of symbols in Σ. The length of a string x, denoted by $|x|$, represents the number of symbols in x. The Kleene closure of Σ, denoted by $\Sigma^\star$, is the set of all finite-length strings of events including the null string ϵ. Throughout the paper, σ or τ is used to denote a symbol in Σ and x, y, z are referred to strings. Let $\{*x\}$ denote the set of all strings with suffix x in $\Sigma^\star$. The set of all strings of length $d \in \mathbb{N}$ over Σ is denoted as Σ^d.

Definition 2.1 (PFSA): A probabilistic finite state automaton (PFSA) is a tuple $\mathcal{L} = (Q, \Sigma, \delta, q_0, \tilde{\pi})$, where

- Q is a (nonempty) finite set, called set of states;
- Σ is a (nonempty) finite set, called input alphabet;
- $\delta : Q \times \Sigma \to Q$ is the state transition function;
- $q_0 \in Q$ is the start state;
- $\tilde{\pi} : Q \times \Sigma \to [0, 1]$ is an output mapping which is known as a probability morph function (or matrix) and satisfies the condition $\sum_{\sigma \in \Sigma} \tilde{\pi}(q_j, \sigma) = 1$ for all $q_j \in Q$.

The basic idea of using a symbolic approach for pattern recognition (called *symbolic dynamic filtering* (SDF) [17]) is the following. The observed or pre-processed time-series data from the physical process are converted to a symbol sequence based on some partitioning technique with the proper choice of the alphabet. Then the tools of computational mechanics, such as D-Markov [18] and CSSR [19], are used to identify statistical patterns of these symbol sequences through construction of a PFSA for each symbol sequence. Transition probability matrices of a PFSA capture the underlying pattern of the physical process, generating the symbol sequences, in the slow scale. During the training phase, a pattern library consisting of reference patterns, modeled as PFSAs, is obtained from the physical processes of interest. In the operational phase, PFSA are constructed from the observed processes. The corresponding transition probability matrices are compared with an appropriate metric (e.g. ℓ_2-norm) to discover how close a particular pattern is to the set of reference patterns in the pattern library.

B. Fusion architecture

Let $\mathbb{L} = \{\mathcal{L}_1, \mathcal{L}_2, \ldots, \mathcal{L}_N\}$ be the universal set of *atomic* patterns. The *atomic* pattern library $\mathbb{L}$ is set of modal footprints identified from individual sensing modalities for various objects or events discovered via PFSA construction. Given the atomic pattern library, a popular framework for addressing information fusion for object and situation assessment is what we call the *set-theoretic* approach. In this framework, higher level patterns, events and scenes or contexts are modeled as subsets of $\mathbb{L}$. Thus a composite pattern, representing an object or even an event, is a collection of elements from $\mathbb{L}$ and the composite pattern library is defined as $\mathbb{L}^* \subset 2^{\mathbb{L}}$. A set-theoretic approach to information fusion that is based on the DFIG information fusion model is shown in Figure 2. Objects (at level 1) are thought of as a collection of atomic patterns and scenes or situations as a collection of objects.

The disadvantage of this approach is that it considers only modal footprints for constructing composite patterns as a *bag of atomic patterns*; relational dependencies, if any, between patterns are disregarded. In the proposed framework, it is assumed that objects are not just a collection of modal footprints but they also contain certain dependencies between the footprints that must be included in their representation. Similarly, the overall situation cannot be modeled as a collection of objects present but must also include relational dependencies between objects.

Our hierarchical semantic framework for object and situation assessment that is inspired from the DFIG information fusion model is shown in Figure 3. The objective is to have a common approach to information fusion going from one level to another and to include relational dependencies for composite pattern representation. In the proposed hierarchy, the lowest level consists of *atomic patterns* identified as PFSAs. These automata are constructed by working in the symbol space that is generated by converting sensor data time series to symbol sequences via phase space partitioning. The middle layer consists of composite patterns for objects that are identified as a structured set that contains atomic patterns and *relationships* between them. These relationships are modeled as cross-dependence between sensor data streams using a *relational* finite state machine. Situations are modeled as objects and relationships between these objects are modeled in a similar fashion using finite state machines. Machines for scene representation work on a higher level and use object-labeled temporal sequences of symbols generated by object dynamics. This top level essentially contains description of scenarios modeled as probabilistic finite state machines that have events and objects for its symbol sequences.

Composite pattern representation form the key feature of the proposed model, that is used for modeling both objects using atomic patterns and scene using objects and events. A composite pattern is defined as a structured set or a *digraph* to include both the constituent units and relations between them. A formal definition is as follows:

Definition 2.2 (Composite pattern representation): Let $\mathbb{L} = \{\mathcal{L}_1, \mathcal{L}_2, \ldots, \mathcal{L}_N\}$ be the atomic pattern library. Let $\mathbb{L}^* \subset 2^{\mathbb{L}}$ be the set of allowable primitives for a scenario. Then a composite pattern library $\mathbb{H}^r = \{\mathcal{H}_1^r, \mathcal{H}_2^r, \ldots, \mathcal{H}_M^r\}$ where a composite pattern $\mathcal{H}_i^r$ is digraph $\mathcal{H}_i^r = (\mathcal{L}_{V_i}, \mathcal{E}_{V_i})$; $\mathcal{L}_{V_i} \subset \mathbb{L}^*$ with the index set $V_i \subset \{1, 2, \ldots, N\}$ and $\mathcal{E}_{V_i} = \{\mathcal{R}_{jk} | (j,k) \in V_i \times V_i\}$ is a set of *relational* PFSAs where: (see Figure 4)

- the digraph for the composite pattern has atomic patterns modeled as PFSAs for its nodes;
- relational dependencies between these nodes are modeled as *relational* probabilistic state machines $\mathcal{R}$ (relational PFSAs);
- relational PFSAs are discovered using xD-Markov machine construction to determine co-dependence. (Note: xD-Markov is pronounced *cross D-Markov*)

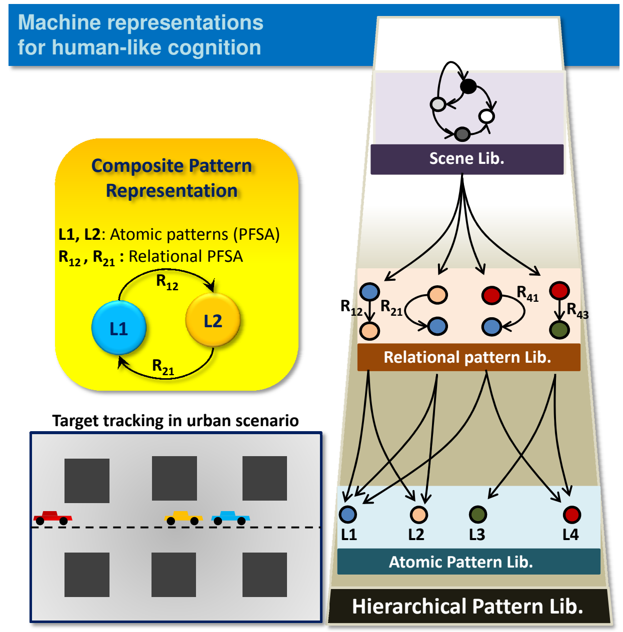

Fig. 3. Proposed semantic framework for information fusion via hierarchical pattern composition using relationship identification.

C. The xD-Markov machine

Definition 2.3: Given two symbol streams $\mathbb{S}^1 = \{s_i^1\}_{i=1}^K$ over the alphabet Σ_1 and $\mathbb{S}^2 = \{s_i^2\}_{i=1}^K$ over the alphabet Σ_2, the d-th order xD-Markov machine that predicts $\mathbb{S}_2$ by observing $\mathbb{S}_1$ is constructed as a tuple $\mathcal{M}_{12} \triangleq (\mathcal{Q}, \mathcal{A}_2, \delta, \widetilde{\Pi})$ such that:

- the state set $\mathcal{Q} = \{q = \{*x\} : x \in \Sigma_1^d\}$;
- the transition map $\delta : \mathcal{Q} \times \Sigma_1 \to \mathcal{Q}$ is defined as

$$\delta(\{*x\}, \sigma) = \{*y\} \tag{1}$$

  if y is the last d symbols of the $x\sigma$, where $x\sigma$ is the concatenation of x and σ.
- the (probability) morph matrix $\widetilde{\Pi} : \mathcal{Q} \times \Sigma_2 \to [0,1]$ is

$$\widetilde{\Pi}(\{*x\}, \tau) = \frac{|\{i : s_i^1 s_{i+1}^1 \ldots s_{i+d-1}^1 = x, s_{i+d}^2 = \tau\}|}{|\{i : s_i^1 s_{i+1}^1 \ldots s_{i+d-1}^1 = x\}|} \tag{2}$$

  where $1 \leq i \leq K - d$.

The xD-Markov algorithm looks similar to the D-Markov algorithm of PFSA construction reported in [18]. Each state q in the d-th order xD-Markov machine is uniquely labeled with a string x of length d. Every string with a suffix x goes into the state q and this defines the transition map. However, the difference lies in the domain of the morph matrix $\widetilde{\Pi}$, which is over Σ_2 rather than Σ_1. The meaning of $\widetilde{\Pi}(\{*x\}, \tau)$ in Equation 2 is the relative frequency of generating the next symbol $\tau \in \Sigma_2$ in $\mathbb{S}_2$ given that a string $x \in \Sigma_1^d$ is observed in $\mathbb{S}_1$. Note: It is assumed that the symbol rate i.e. the number of symbols per unit time or time discretization , is approximately the same for both symbol streams $\mathbb{S}_1$ and $\mathbb{S}_2$. Relational machine construction for mismatched symbol rate can be addressed by using the finer of the time discretizations

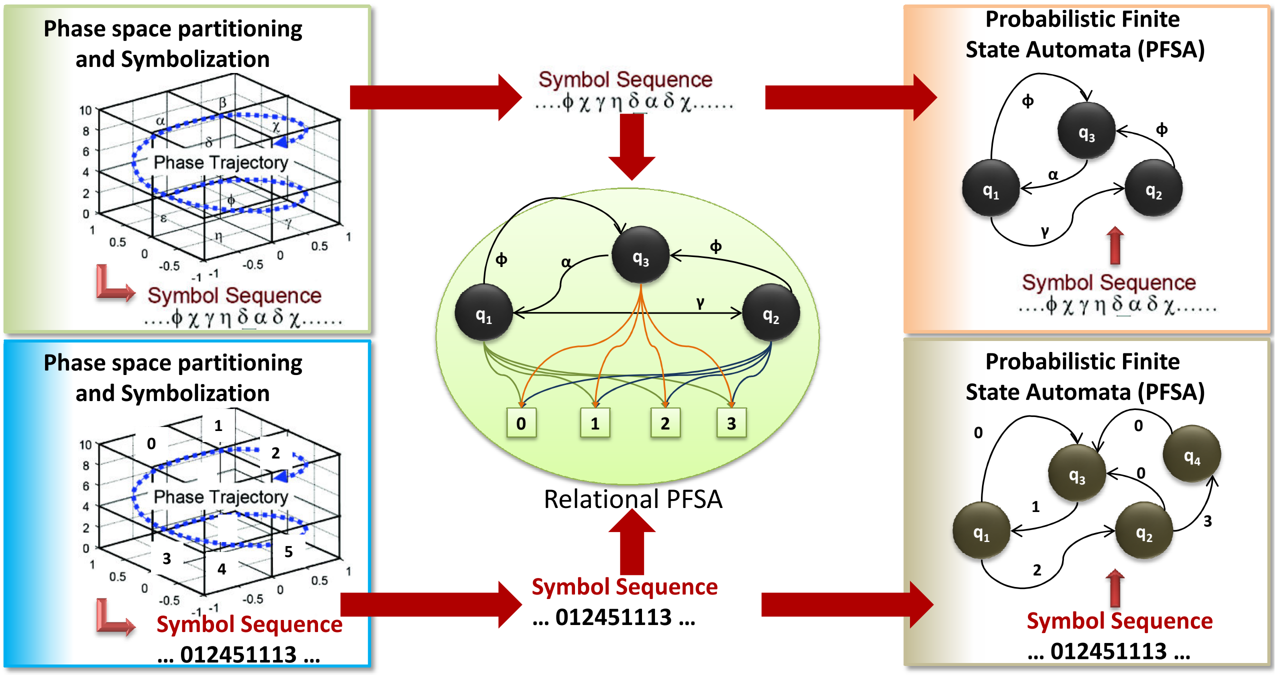

Fig. 4. General construction algorithm for the xD-Markov machine

for $\mathbb{S}_1$ and $\mathbb{S}_2$; effects of such a symbol rate mismatch would be explored as future work.

The xD-Markov machines, as outputs of the xD-Markov algorithm, are not PFSA in the sense of Definition 2.1. Mathematically, the xD-Markov machines are exactly the hidden Markov models (HMM) [20] with Σ_1 and Σ_2 as input and output alphabet, respectively. However, as opposed to HMM, the state sequence of a xD-Markov machine is not hidden since the state sequence is observed in the symbol stream $\mathbb{S}^1$ over $\mathcal{A}_1$. Thus the xD-Markov algorithm can be regarded as a special case of learning algorithms of HMM, which predicts the (output) symbol distribution in $\mathbb{S}^2$ given the knowledge of the observed states from $\mathbb{S}^1$. Figure 4 schematically describes the algorithm for xD-Markov machine construction.

The set-theoretic approach falls at one end of the spectrum for modeling complex objects and scenes that cannot be represented or observed in a single sensing modality or using a single sensor. In this approach, all relationships are excluded and any fusion is solely done in the *decision-theoretic* sense where the presence (or absence) of one or more footprints is used to estimate the label of the object under consideration (e.g. Bayesian classification). The other end of the spectrum is to fuse data at the lowest level and extract features (e.g. by constructing PFSAs) working in the product space of all sensors. This approach would be able to extract modal dependencies before they are lost when constructing separate machines for individual sensor or modalities. But working in the product space has the danger of state space explosion especially when the sensors and sensing modalities can be numerous, which is the case of a sensor network. The proposed approach is a trade-off between the two ends of the spectrum and attempts to include relational dependencies between sensing modalities, while keeping it tractable for a practical application. A hierarchical approach ensures that composite patterns are identified only when their constituting units at the lower level have been observed. In the current framework we have considered relations taken only two at a time, but we propose to explore relations between higher order cliques as future work.

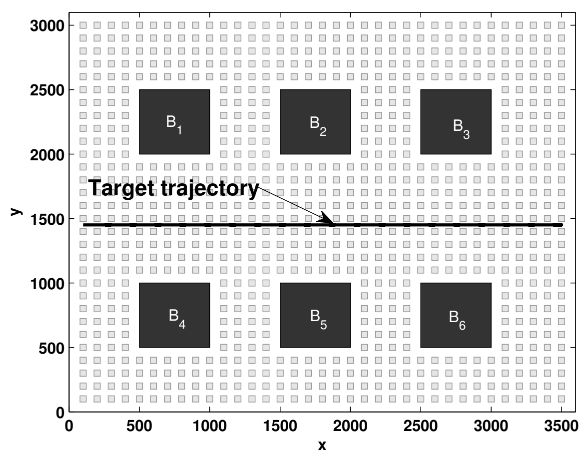

Fig. 5. Simulation set-up containing sensors (grey squares), target trajectory (black line) and buildings (B_i)

III. TARGET IDENTIFICATION

This section presents the results of target identification done in an urban scenario using the proposed framework. The urban sensor network scenario is set up by creating an environment containing blocks of buildings ($B_i, i = 1, 2, \ldots$ in Figure 5) placed as *manhattan* blocks with a sensor nodes distributed in a grid surrounding these blocks. The sensor network is made up of an equally-spaced grid of acoustic sensors. The detected acoustic signature is filtered into the high frequency component and the low frequency component

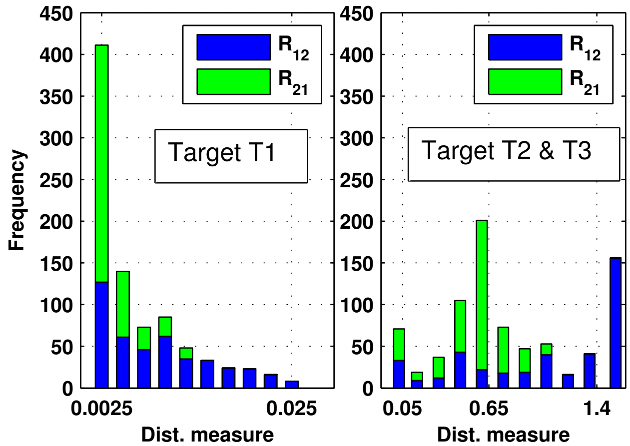

Fig. 6. Distribution of distance measure $d(\widetilde{\Pi}, \widetilde{\Pi}_0)$ generated by comparing the observed $\widetilde{\Pi}$ matrix with a reference $\widetilde{\Pi}_0$.

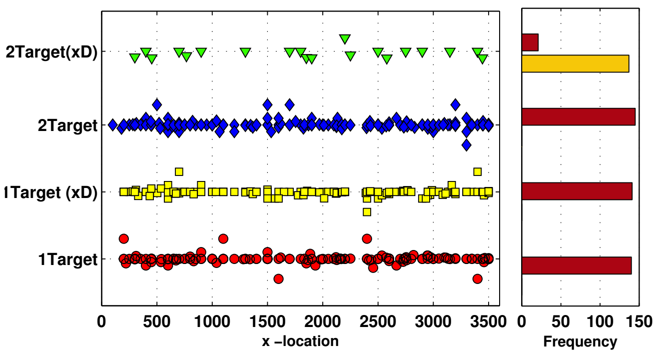

Fig. 7. Estimated location ($\boldsymbol{T}_1$) and detection frequency for four cases: (1) one target ($\boldsymbol{T}_1$) with both atomic patterns $\mathcal{L}_1$ and $\mathcal{L}_2$ and *set-theoretic* identification (red circles); (2) one target ($\boldsymbol{T}_1$) with both atomic patterns $\mathcal{L}_1$ and $\mathcal{L}_2$ and xD-Markov -based identification (yellow squares); (3) two targets ($\boldsymbol{T}_2$ & $\boldsymbol{T}_3$) with atomic patterns ($\mathcal{L}_1$) and ($\mathcal{L}_2$) respectively and *set theoretic approach* identification (blue diamonds) and (4) two targets ($\boldsymbol{T}_2$ & $\boldsymbol{T}_3$) with atomic patterns ($\mathcal{L}_1$) and ($\mathcal{L}_2$) respectively and xD-Markov -based identification (green triangles). Bar chart shows the number of detections identified as $\boldsymbol{T}_1$ (red) or $\neg\boldsymbol{T}_1$ for *not* $\boldsymbol{T}_1$ (yellow) for set-theoretic and proposed approach (xD). Note: location is estimated only when target is identified as $\boldsymbol{T}_1$.

on each sensor node (*data assessment*). Signatures of interest in each frequency band are extracted as PFSA using the D-Markov machine (Section II-A): these modal (atomic) footprints are $\mathcal{L}_1$ for the high frequency component and $\mathcal{L}_2$ for the low frequency component.

A target of interest ($\boldsymbol{T}_1$)(possibly malicious) is assumed to carry both modal footprints $\mathcal{L}_1$ and $\mathcal{L}_2$. The goal is to identify a target $\boldsymbol{T}_1$ in an urban scenario where targets with footprints $\mathcal{L}_1$ only ($\boldsymbol{T}_2$) and $\mathcal{L}_2$ only ($\boldsymbol{T}_3$) can also be present. This is a representative model of an urban scenario where chance co-occurrence of targets would be the norm rather than an exception.

We model a target object using the proposed framework as a composite pattern and define the composite pattern library $\mathbb{H}^r = \{\mathcal{H}_1^r, \ldots, \mathcal{H}_4^r\}$ as follows: $\boldsymbol{T}_1$ is represented as a composite pattern $\mathcal{H}_1^r = (\mathcal{L}_1, \mathcal{L}_2; \mathcal{R}_{12}, \mathcal{R}_{21})$, where $\mathcal{R}_{12}$ and $\mathcal{R}_{21}$ are relational PFSA. Targets $\boldsymbol{T}_2$ and $\boldsymbol{T}_3$ are modeled as $\mathcal{H}_2^r = (\mathcal{L}_1)$ and $\mathcal{H}_3^r = (\mathcal{L}_2)$ respectively. While a situation where $\boldsymbol{T}_2$ and $\boldsymbol{T}_3$ are both present in the environment is modeled as $\mathcal{H}_4^r = (\mathcal{L}_1, \mathcal{L}_2; \emptyset, \emptyset)$, where absence of relational patterns $\mathcal{R}_{12}$ and $\mathcal{R}_{21}$ is denoted by $\emptyset$.

Following the methodology given in Section II-A, atomic patterns are constructed via the D-Markov algorithm with an alphabet size of four ($|\mathcal{A}| = 4$) and depth (D) of one. The *relational* patterns are extracted by the xD-Markov algorithm with depth value set to one. During the training phase, atomic patterns $\mathcal{L}_1^0$ and $\mathcal{L}_2^0$ and relational patterns $\mathcal{R}_{12}^0$ and $\mathcal{R}_{21}^0$ are obtained. We show that the previous frameworks based on the set-theoretic approach do not distinguish between a single target vehicle with both pattern $\mathcal{L}_1$ and $\mathcal{L}_2$, and two separate vehicles moving together, one with the pattern $\mathcal{L}_1$ and one with pattern $\mathcal{L}_2$; while such scenarios can be distinguished within our proposed framework.

Figure 6 show the distribution of distance measure $d(\widetilde{\Pi}, \widetilde{\Pi}_0)$ when one target with both atomic patterns ($\mathcal{L}_1$ & $\mathcal{L}_2$), and two targets moving closely, with atomic patterns ($\mathcal{L}_1$) and ($\mathcal{L}_2$) respectively, are observed in the environment. The measure $d(\widetilde{\Pi}, \widetilde{\Pi}_0)$ is computed as the ℓ_2-norm distance between the morph matrix of the detected pattern, $\widetilde{\Pi}$, and that of the reference pattern $\widetilde{\Pi}_0$. It can be clearly seen from the bar plots of the distribution of the distance measure that a simple threshold on the chosen distance measure can be used to distinguish the two cases. In this example, the thresholds of the atomic patterns are chosen to be the same $\alpha = 0.012$ and those of the relational patterns are $\alpha_{12} = 0.025$ and $\alpha_{21} = 0.0125$, respectively.

When running the urban scenario, acoustic signals emitted from the vehicles are sampled by individual sensor nodes to collect 5000 samples. Due to background noise, SNR drops quickly with distance from the target and only nearby sensor nodes are able to record any meaningful signal. An inter-node distance of 100 units ensures a fully covered field with minimal sensor nodes for a grid placement. Sensor data is transformed into a symbol sequence (using $|\mathcal{A}| = 4$) at each node which is used to create atomic and relational patterns. In general, if a pattern (atomic or relational) closely resembles its corresponding reference pattern when compared using the ℓ_2 distance measure d, then that component of the composite pattern $\mathcal{H}_i^r$ is said to be detected. Only if both atomic signatures are detected, the two relational patterns $\mathcal{R}_{12}$ and $\mathcal{R}_{21}$ are extracted for the cross dependence between symbol sequences. They are compared with their corresponding reference $\mathcal{R}_{12}^0$ and $\mathcal{R}_{21}^0$. At this point, if both relational patterns are matched, then the sensor declares the detection of the composite pattern $\mathcal{H}_1^r$ for target $\boldsymbol{T}_1$ and its position estimation is done via multilateration.

The results of target identification are shown for four cases in Figure 7 where the estimated location and detection frequency are shown for four cases. As mentioned earlier, the location is estimation only when sensor nodes identify the target as $\boldsymbol{T}_1$. The four cases are: (1) one target ($\boldsymbol{T}_1$) with both atomic patterns $\mathcal{L}_1$ and $\mathcal{L}_2$ and identification done using *set-theoretic* approach for composite pattern representation (red circles); (2) one target ($\boldsymbol{T}_1$) with both atomic patterns $\mathcal{L}_1$ and $\mathcal{L}_2$ and identification done using proposed approach for composite pattern representation (yellow squares); (3) two targets ($\boldsymbol{T}_2$ & $\boldsymbol{T}_3$) with atomic patterns ($\mathcal{L}_1$) and ($\mathcal{L}_2$) respectively moving close to each other in the sensor field and identification is done using the set theoretic approach (blue diamonds) and (4) two targets ($\boldsymbol{T}_2$ & $\boldsymbol{T}_3$) with atomic patterns ($\mathcal{L}_1$) and ($\mathcal{L}_2$) respectively moving close to each other in the sensor field and identification is done using the proposed approach (green triangles).

Figure 7 also shows the number of detections identified as $\boldsymbol{T}_1$ (red) or $\neg\boldsymbol{T}_1$ for *not* $\boldsymbol{T}_1$ (yellow) for set-theoretic and proposed approach (xD). The false alarm rate in the two target case and the set theoretic approach is a full 100%. This is expected since the set-theoretic approach disregards relational dependence between patterns and is therefore confuses co-occurrence of targets $\boldsymbol{T}_2$ and $\boldsymbol{T}_3$ with the presence of $\boldsymbol{T}_1$. On the other hand, the false alarm rate with our approach is 13.3%. The performance of the object and situation assessment is greatly improved in this example by use of the relational PFSA to capture dependence between the atomic patterns. Also, it can be seen that utilization of the proposed methodology did not lead to any noticeable decrease in the detection frequency of the one target with both pattern case ($\boldsymbol{T}_1$).

IV. Conclusion and Future Work

A data-driven semantic framework is proposed for object assessment and situation assessment in sensor networks in the context of the Data Fusion Information Group (DFIG) model. Distinct from the set-theoretic approach, the xD-Markov algorithm is introduced to extract the cross-dependencies among the objects as relational PFSA. Situations are classified based on both atomic PFSA and relational PFSA. A target identification application shows that, in comparison to the set-theoretic approach, the proposed approach for composite pattern representation with relational PFSA significantly improves the false alarm rate in a sensor network. Moreover, it provides for a tractable approach, particularly suited for sensor networks for onboard processing, that has the ability to capture the relational dependence between data streams.

To enhance the performance of the xD-Markov algorithm, the following issues are suggested to be addressed as future work.

- Similar to the model structure selection procedure for D-Markov machines proposed earlier in [18], [21], [22], a methodology for depth selection is required for the xD-Markov machine during the training phase.
- Partitioning for symbol sequence generation is currently done to suit the extraction of unimodal patterns using the D-Markov machine. However, partitioning methods may need to be adapted for relational PFSA construction using the xD-Markov algorithm.
- The robustness of the xD-Markov algorithm for relational PFSA construction to the phase shifts in the input symbol sequences and mismatched symbol rates should be investigated.
- Higher order cliques (≥ 2) for relationship identification between atomic patterns should be considered.
- Experimental validation and online testing of the proposed methodology.

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