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Temporal uncertainty reasoning networks for evidence fusion with applications to object detection and tracking

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Abstract

In this paper, we present a temporal uncertainty-based inferencing paradigm for sensor networks. Multiple sensors observe a phenomenon and then exchange their probability estimates (for the occurrence of an event) with each other. Each node in the network fuses the evidence in such received messages, and computes the probability of occurrence of the relevant event. We develop and apply a temporal relevance decay model that accounts for the possibility that some observations lose their relevance or importance with the passage of time. As an illustrative example, this model is applied to the problems of object detection and tracking using multiple sensors with varying degrees of reliability.

Keywords: Bayesian networks; Temporal reasoning; Evidence fusion; Object detection; Tracking

1. Introduction

Bayesian networks [1,2] provide an important framework for information fusion, using evidence available from observations (such as sensors) as well as prior knowledge extracted from other sources. Concurrent learning while combining knowledge can be accomplished by the use of learning algorithms to estimate various prior and conditional probabilities from data acquired as the system is being used, such as the algorithms of [3,4]. However, the development of an efficient representation and the design of associated algorithms are challenging tasks when the knowledge to be combined represents time-varying relationships. In such circumstances, the arrival of different pieces of evidence as well as the reasoning steps occur asynchronously, over continuous time; knowledge of the relevant time instants is then crucial in determining the belief (a posteriori probability) associated with high level hypotheses. This motivates the research reported in this paper. We begin with methodological questions: what kind of efficient representations and inferencing algorithms will permit reasoning with uncertainty over continuous time, drawing conclusions about the state of a system or target, based on uncertain evidence that arrives asynchronously from multiple sources, whose reliability and relevance depend on the time of observation as well as the time of inference?

Sensor networks are increasingly being used for object detection and tracking in surveillance applications. For information fusion in the context of a decision-making scenario, the observations from multiple sensors may be unreliable as well as associated with different timestamps, and may arrive at fusion nodes at different points in time. Further, the relevance of these observations may change between the time of observation and the time at which an inference is made by the fusion node. A "time-blind" fusion procedure is likely to make significant errors in processing information in such situations. This paper formulates a *Temporal Uncertainty Reasoning Network* (TURN) methodology that updates conditional probabilities taking into account the timestamp associated with observations as

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well as the time point at which belief computation is to be carried out. Temporal relevance decay models with a small number of parameters are constructed, which are applicable in a large variety of applications. The underlying model is a network whose nodes represent variables that take on values from a discrete set, and links or edges represent probabilistic relationships between the variables. Our focus is on asynchronous information fusion, where time delays must be taken into account as information and evidence propagate from evidential nodes to fusion nodes. We consider two cases: (1) the *relative case* focusing on the time difference between the observation and the fusion events; and (2) the *absolute* case focusing on the precise instants when observations and fusion occur.

Example: Decision-making in a battlefield context exemplifies such a problem. The goal is to infer the probability of the presence of a target, based on the reports of different local processors that draw their conclusion based on various sensor readings, as illustrated in Fig. 1. Note that some sensor readings may be accessible to multiple processors. In addition to detections, local processor reports may include location, velocity and quantity information and the processors themselves may make inferences, drawing on additional knowledge not present at the sensors, e.g., recognizing patterns from the pixels lighted on their screens that depict possible vehicle tracks.

Processors may send non-identical reports at different points in time, reflecting the reality that the target being observed is itself dynamically changing in position, velocity, quantity and other observable or inferable characteristics. Further, each of these reports may be associated with different reliability characteristics that depend on time. The prior probability of the phenomenon of interest (being observed or inferred) may change with time; for example, a military attack may be more likely at dawn than at noon. The reliability of some observations may be affected by visibility, which depends on time. In addition, more recently arriving information is expected to be more reliable than earlier information. These temporal effects are extremely important when the inferences are carried out leading to final decisions.

Section 2 discusses the background for the research in this paper, i.e., Bayesian networks and reasoning with time. The foundations of the new approach presented in this paper are discussed in Section 3. Section 4 formulates the decay model for the relative case. Section 5 presents an example application of this model, viz., target tracking. Section 6 formulates the model for the absolute case, with an application. Section 7 summarizes this paper and discusses future work.

2. Background

Bayesian methods provide a way for reasoning about partial beliefs under conditions of uncertainty using a probabilistic model, encoding probabilistic information that permits us to compute the probability of a well-formed sentence (or event). The main principle of Bayesian techniques lies in the celebrated inversion formula:

$$P(H|e) = \frac{P(e|H)P(H)}{P(e)} \tag{1}$$

where $P(e|H)$ is the likelihood, $P(H)$ is called the prior probability, $P(H|e)$ is the posterior probability, and $P(e)$ is the probability of evidence. *Belief* associated with the hypothesis H is updated based on this formula when new evidence arrives. This approach forms the basis for reasoning with Bayesian *causal networks*, discussed in Section 2.1, and extended to reasoning with temporal uncertainty using approaches that are discussed in Section 2.2.

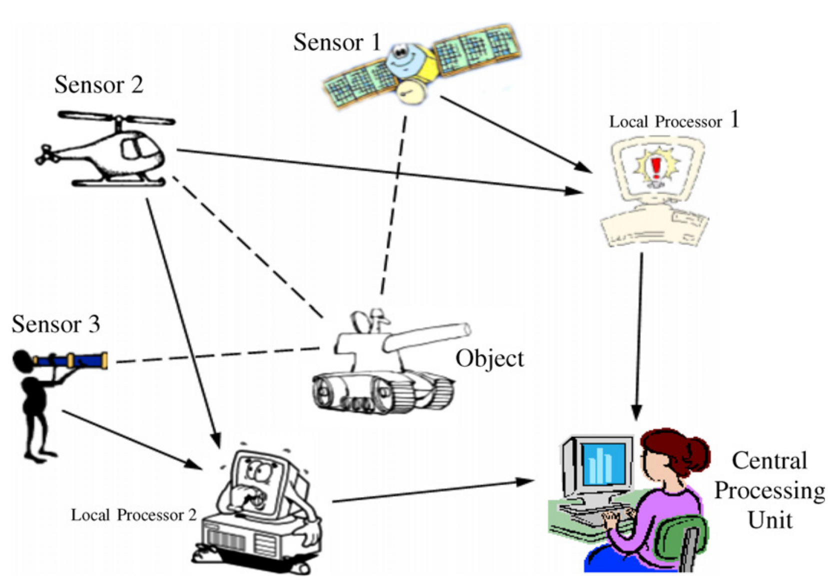

Fig. 1. Decision-making in a battlefield scenario.