Multi-sensor fusion through adaptive bayesian networks

Article

Accepted version

A. De Paola, S. Gaglio, G. Lo Re, M. Ortolani

In AI*IA 2011: Artificial Intelligence Around Man and Beyond, 2011, pp. 360-371

Publisher: Springer

http://link.springer.com/chapter/10.1007%2F978-3-642-23954-0_33

Multi-sensor Fusion through Adaptive Bayesian Networks

Alessandra De Paola, Salvatore Gaglio, Giuseppe Lo Re, and Marco Ortolani

University of Palermo
Viale delle Scienze, ed 6. – 90128 Palermo, Italy
{depaola, gaglio, lore, ortolani}@unipa.it

Abstract. Common sensory devices for measuring environmental data are typically heterogeneous, and present strict energy constraints; moreover, they are likely affected by noise, and their behavior may vary across time. Bayesian Networks constitute a suitable tool for pre-processing such data before performing more refined artificial reasoning; the approach proposed here aims at obtaining the best trade-off between performance and cost, by adapting the operating mode of the underlying sensory devices. Moreover, self-configuration of the nodes providing the evidence to the Bayesian network is carried out by means of an on-line multi-objective optimization.

Keywords: Ambient Intelligence, Bayesian Networks, Multi-objective optimization

1 Motivations and Related Work

Artificial reasoning in many real world scenarios relies on measurements collected from diverse sensory sources; commonly available devices are typically affected by noise, and characterized by heterogeneity as regards their energy requirements; moreover their behavior may vary across time.

One of the application scenarios of artificial intelligence where multi-sensor data fusion is particularly relevant is Ambient Intelligence (AmI). The AmI paradigm relies on the capability of sensing the environment, through the deployment of a pervasive and ubiquitous sensory infrastructure, surrounding the user, for monitoring relevant ambient features. Among these, a high attention is devoted to context information, such as the users' presence in monitored areas or current users' activities [9,6,2].

In our work, we present a sample scenario of an AmI system devoted to detect users' presence through a wide set of simple and low-cost devices, possibly affected by a non negligible degree of uncertainty, as well as devices capable of measuring environmental features only partially related to the human presence, and finally a limited set of more precise, though more expensive sensors. In particular, we suppose that the sensory infrastructure is embodied into a Wireless Sensor Network (WSN) [1], whose nodes, pervasively deployed in the environment, are capable of on-board computing functionalities and are characterized by limited, non-renewable, energy resources.

In order to estimate the environmental features of interest, while keeping the sensor nodes operating costs low, we propose a system that fully exploits the intrinsic statistical dependencies in the available sensory readings and copes with their inherent uncertainty by performing a multi-sensor data fusion.

Few works in literature propose a real multi-sensor data fusion framework for Ambient Intelligence. Remarkable exceptions are works presented in [5] and [7]. The authors of [5] propose a multi-sensor fusion system for integrating heterogeneous sensory information in order to perform user activity monitoring. The authors present a comparison between two probabilistic approaches (Hidden Markov Models, and Conditional Random Fields), and point out the effectiveness of a probabilistic system for activity detection in terms of dealing with uncertainty. The authors of [7] present an activity recognition approach reinforced by information about users' location. The proposed framework uses a variety of multimodal and unobtrusive wireless sensors integrated into everyday objects; this sensory infrastructure provides data to an enhanced Bayesian Network fusion engine able to select the most informative features.

Unlike other works reported in literature, the work presented here focuses on the dynamic management of the devices providing information to the inference system, thus allowing to deal with such conflicting goals as energy saving and accuracy of the outcome. In particular, the proposed system comprises two levels of reasoning; at the low level a Bayesian network for reasoning on the relevant environmental feature (such as users' presence), merges the available sensory data, while the upper level performs a meta-reasoning on system performance and cost. This meta-level is able to trade the reliability of the Bayesian network outcome for the relative cost in terms of consumed energy, in order to steer a decision about which sensory devices are to be activated or de-activated.

The remainder of the paper is organized as follows. Section 2 presents the general architecture of the proposed system, while Section 3 details its self-configuration capability. The self-configuration process is illustrated through a running example in Section 4 and finally Section 5 reports our conclusions.

2 The Proposed System

One of the requirements characterizing AmI is the availability of a pervasive sensory infrastructure characterized by a low cost and general as much as possible. For this reason, often, reasonings about context are not be performed via specialized sensors, so that the sensed signals will only be partially correlated to the features of interest.

In order to correctly infer the presence of users from the available sensory information a Bayesian inference system for multi-sensor data fusion has been developed. Probabilistic reasoning accounts for the partial correlation between sensory signals and states, and allows to cope with noisy data. The possibility of integrating data coming from multiple sensors exploits the redundancy of such devices deployed throughout the environment.

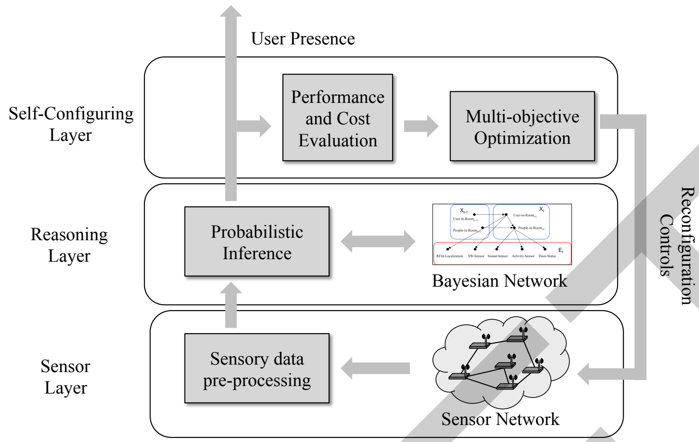


Fig. 1. Block diagram for the presence estimate system.

On top of the Bayesian network, a meta-level for self-configuration is implemented, as shown in Figure 1. Such higher level component reasons about potential trade-offs between the confidence degree of the Bayesian network and the cost for using the sensory infrastructure. A plan will be produced stating which sensory devices are to be activated or de-activated.

2.1 The Sensory Infrastructure

The proposed system was developed by taking an existing AmI software architecture as a reference; the original AmI architecture has been implemented at our department and is described in [3].

The sensor network used for our AmI architecture is composed by several heterogeneous devices capable of capturing different physical phenomena. In particular, here we consider five kinds of sensory technologies: WSN, RFId readers, door sensors, sensors on actuators and software sensors.

WSN are composed by small computing devices equipped with off-the-shelf sensors for measuring ambient quantities and with wireless transceivers that enable data exchange among nearby nodes [1]. Sensor nodes in our AmI architecture have been deployed in various rooms close to "sensitive" indoor areas: by the door, by the window, and by the user's desk.

When considering the specific task of user presence detection, we will consider in particular the sound sensor, which is able to detect the amount of noise level in its proximity, thus providing some rough indication about the level of room occupancy.

Other nodes carry specific sensors, such as RFId readers, in order to perform basic access control. In the considered scenario, RFId tags are embedded into ID badges for the department personnel, while RFId readers are installed close to the main entrance and to each office door; readings from each tag are collected via the relative nodes, and forwarded by the WSN to the AmI system, that will process them and will reason about the presence of users in the different areas of the department.

Besides being equipped with a RFId reader, each entrance to the building will also be coupled to a sensor recording its status (i.e. if it is open, closed or locked), which may be used for monitoring access to the different areas, as well as for extracting information about the presence of people.

The interaction of users with the actuators may also be captured via ad-hoc "monitors"; for instance, if the user manually triggers any of the provided actuators (e.g. the air conditioning, the motorized electric curtains, or the lighting systems) via the remote controls or traditional switches, specialized sensors capture the relative IR or electric signals. Detecting some kind of interaction provides a reliable indication about the presence of at least one person in the monitored area.

Finally, a "software sensor" is installed on the users' personal computers to keep track of user login and logout, and to monitor their activity on the terminal. As long as users are actively using their terminal, such sensors will set the value for the probability of the user to be present to its maximum. On the other hand, if no activity is detected, the presence of users close to their workstations may still be inferred via a simple face recognition application, which may be triggered to refine the probability value of user presence based on a degree of confidence in the identification process.

2.2 Environmental Modeling through a Bayesian Network

A system aimed at inferring information about a specific environmental feature based on data coming from multiple sensors may be easily implemented through a rule-based approach, in cases where the sensory information is not affected by noise and uncertainty. Otherwise, the reasoning system needs to take uncertainty into account, as is the case with user's presence detection based on the sensory data mentioned earlier. In such cases, Bayesian Network theory [8] may be an optimal choice for inferring knowledge through a probabilistic process, since it provides an effective way to deal with the unpredictable ambiguities arising from the use of multiple sensors [7].

Classical Bayesian networks, however, may only provide a static model for the environment, which would not be suitable for the proposed scenario; we therefore chose dynamic Bayesian networks or, more specifically, Markov chains to implement our model, which thus allow for probabilistic reasoning on dynamic scenarios, where the estimate of the current system state depends not only on the instantaneous observations, but also on past states.

Figure 2(a) shows the Bayesian network used to infer probabilistic knowledge on a given state feature based on a set of input sensory data. Each state feature affects a set of sensory readings (we indicate each evidence node with E^i), that can be considered the perceivable manifestation of that state. The connection between the current state and its sensory manifestation is given by the proba-

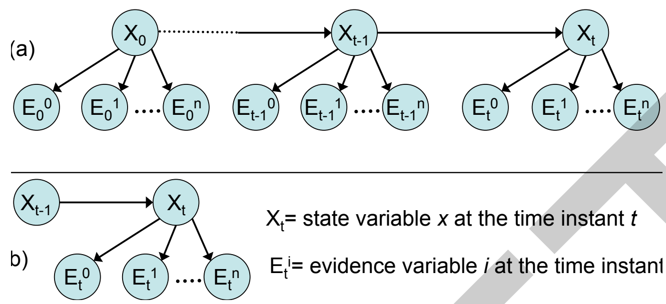


Fig. 2. Structure of a Markov chain for inferring a given state feature starting from a set of sensory data.

bilistic sensor model $P(E_t^i|X_t)$. Moreover the current state depends on past state according to a state transition probability $P(X_t|X_{t-1})$.

The belief about the specific value of a state variable is the conditional probability with respect to the whole set of observations from the initial time to the current time:

$$\begin{aligned} Bel(x_t) &= P(x_t|e_1^1, e_1^2, \ldots, e_1^n, \ldots e_t^1, e_t^2, \ldots, e_t^n) = \\ &= P(x_t|\mathbf{E}_1, \mathbf{E}_2, \ldots, \mathbf{E}_t) = P(x_t|\mathbf{E}_{1:t}) \ . \end{aligned} \tag{1}$$

Due to the simplifications introduced by the Markov assumption, and to the conditional independence among sensory measurements, once the state induced by the Bayesian network is known, the belief about the current state can be inductively defined as follows:

$$Bel(x_t) = \eta \prod_{e_t^i} P(e_t^i|x_t) \cdot \sum_{x_{t-1}} P(x_t|x_{t-1}) Bel(x_{t-1}) \ . \tag{2}$$

Thanks to these simplifications, at each time step it is sufficient to consider a reduced set of variables, as shown in Figure 2(b), which results in a reduced overall computation effort.

3 Implementing Self-configuration

In some circumstances it can be useful to modify the status of the sensory infrastructure because of particular environmental conditions, or in accordance with the current system performances. In other words, it is sometimes desirable to act on the sensory devices by turning them on or off, thus modifying the flow of information feeding the probabilistic reasoner.

The first scenario occurs when the cost of some of the sensory acquisition devices increases; such variation may be caused by the enforcement of specific energy saving policies aiming to increase the WSN lifetime. In this case, each sensor may be tagged with a cost in terms of required energy, inversely proportional to its charge level, and it is preferable for the system to do without these sensory inputs, provided that the performance quality is not affected, or at least that the degradation is deemed acceptable. As a consequence, it should be possible to modify the sensory infrastructure status by allowing such devices to go into a "low consumption" mode, for instance by suspending the sensory data gathering; normal functioning would be restored only for those devices whose contribution is crucial for the probabilistic inference engine.

The second scenario occurs when the Bayesian network receives its input from a greatly reduced set of sensory devices, so that the system is forced to assign a high degree of uncertainty to the environmental states. In such situation, the adoption of an additional sensory device, although very expensive, may contribute to decease the uncertainty degree; therefore, a set of previously de-activated sensory devices may be switched back to normal functioning, so as to provide additional information for the inference process.

Following these considerations, and in order to make the system as self-sufficient as possible, we allow it to autonomously opt to modify the status of the sensory infrastructure, by suspending or restoring the data flow from some evidence nodes, in order to get the best trade-off between energy cost and precision in reasoning.

3.1 Indices for Self-configuration

An extended model of Bayesian network was adopted, where each node is tagged with additional information. In particular, evidence nodes are tagged with two additional pieces of information: cost, and operation mode.

The operation mode gives an indication about the state of the sensory devices associated to the evidence node, i.e. activated or de-activated; for the evidence node E^i, the operation mode at time instant t is indicated as op^i_t.

The cost associated to the evidence nodes is not set within the probabilistic inference system itself, rather it is set by an energy management subsystem based on the current state of the sensor nodes. Based on the costs of the evidence nodes, it is possible to compute the overall cost for a state variable as the sum of the costs of its connected evidence nodes. Such value represents the total cost necessary to infer the distribution probability for the state variable, depending on the currently used sensory information.

Furthermore, assuming that the function for computing the cost of evidence node E^i_t is indicated by $f_{cost}(E^i_t)$, then the following holds:

$$\begin{aligned} cost(E^i_t) &= \begin{cases} f_{cost}(E^i_t) & \text{if } op^i_t \text{ is } on \ , \\ 0 & \text{otherwise} \ ; \end{cases} \\ cost(X_t) &= \sum_{E^i_t \in \mathbf{E_t}} cost(E^i_t) \ . \end{aligned} \tag{3}$$

In order to assess the performance of the current configuration of the Bayesian network it is useful to extract information about the precision of the probabilistic reasoning, besides the overall energy cost. An uncertainty index will be used to measure the intrinsic uncertainty of the a posteriori inferred belief:

$$uncertainty(X_t) \stackrel{def}{=} -\sum_{x_t} Bel(x_t) \log Bel(x_t) \ . \tag{4}$$

Even though the definition of the uncertainty index is formally similar to that of the entropy for variable X, the latter is a function of the *a priori* probability distribution, whereas the uncertainty index is a function of the *a posteriori* probability distribution.

Indices $cost(X_t)$ and $uncertainty(X_t)$ give indications about the cost and effectiveness of the probabilistic reasoning about a state variable X_t.

3.2 Adapting the Sensor Network Configuration

In our model, different configurations of the sensory infrastructure may be completely expressed by indicating the operating mode of each evidence node. The configuration of the entire sensor network may thus be expressed by a vector: $s_t = [op_t^0, \ldots, op_t^i, \ldots, op_t^n]$.

By monitoring the indices for cost and uncertainty for each state variable, according to Equations 3 and 4, the system checks whether the uncertainty index is close to its maximum allowed value and whether the cost index rises unexpectedly. If one of these two events occurs, a modification of the sensory infrastructure is triggered.

In order to avoid oscillations in the configuration of the sensor network and to ensure gradual modifications of its structure, each inference step only enables atomic actions, i.e. actions operating on one evidence node at a time.

In order to select the action to be performed, a multi-objective selection system is devised, based on a Pareto-dominance criterion; the aim is to obtain the best trade-off between cost minimization and uncertainty minimization. As is evident, the two goals are conflicting and minimizing with respect to costs only would lead to deactivating all the sensory devices, whereas minimizing with respect to uncertainty only would lead to activating all of them.

The optimal action is selected with respect to the cost and the hypothetical uncertainty that the system would have obtained for each alternative configuration of sensory devices, considering the actual sensor readings. For a specific configuration s we indicate these indices as $C(s)$ and $U(s)$, respectively; they will be computed by disregarding the evidence nodes corresponding to deactivated sensory devices in Equations 3 and 2.

When dealing with the conflicting goals of minimizing $U(s)$ and $C(s)$, the traditional approach of merging them into a single objective function presents several limitations, mainly because it would require an accurate knowledge of the different objective functions, either in terms of relative priority or relevance. On the contrary, we chose to keep two independent objective functions and to manage them through a multi-objective algorithm.

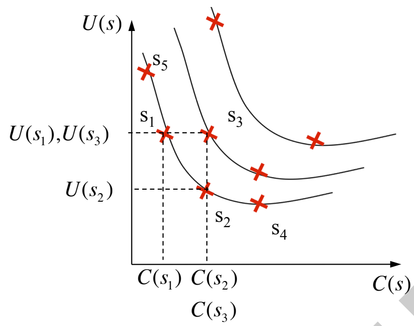


Fig. 3. Graphical example of the Pareto-dominance analysis.

We will say that a configuration s_i *Pareto-dominates* another configuration s_j if:

$$C(s_i) \leq C(s_j) \wedge U(s_i) \leq U(s_j). \tag{5}$$

A configuration s^* is *Pareto-optimal* if no other solution has better values for each objective function, that is if the following holds:

$$\begin{cases} C(s^*) \leq C(s_i) \\ \quad\text{and} \\ U(s^*) \leq U(s_i) \end{cases} \forall i = 1 \ldots n \ . \tag{6}$$

Figure 3 represents an example of the Pareto-dominance analysis: configurations s_1 and s_2 belong to the same non-dominated front because $C(s_1) \leq C(s_2)$ and $U(s_2) \leq U(s_1)$, while both configurations s_1 and s_2 dominate configuration s_3; the set of optimal configurations is $\{s_1, s_2, s_4, s_5\}$.

The Pareto-dominance analysis is performed through the fast non-dominated sorting procedure proposed in [4], whose complexity is $O(mN^2)$, where m is the number of objective functions ($m = 2$ in our case) and N is the number of evidence nodes.

Within the optimal front, the configuration improving the index related to alarm triggering is chosen; namely if $cost(X_t)$ triggered the alarm, the configuration improving index $C(s)$ is selected, whereas if $U(X_t)$ triggered the alarm, the configuration improving index $U(s)$ is selected.

4 Running Example

This section describes a running example illustrating how our self-configuring Bayesian network operates. We will consider a network with one state variable X, with 2 possible different values, and three evidence nodes E^1, E^2, E^3, taking 3, 2 and 2 values respectively; the network is defined through the conditional probabilities tables reported in Tables 1 and 2.

Let us assume that the considered state variable is associated to the presence of the user in her office room and that evidence variables are associated to the

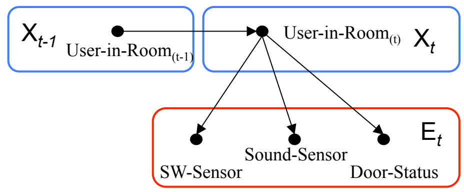


Fig. 4. Bayesian Network for the running example.

software sensor, to the door-status sensor and to the set of sound sensors (see Figure 4).

Let us consider an initial a configuration where all three sensors are active; furthermore let $P(X_0) =< 0.9, 0.1 >$ represent the probability distribution for the state variable at time $t = 0$ (i.e. $P(X_0 = 0) = 0.9$ and $P(X_0 = 1) = 0.1$). For the sake of the example we will assume that the cost associated to evidence variables E^1 and E^2 will not vary over time and will be equal to $cost(E^1) = cost(E^2) = 1$, whereas the cost associated to evidence variable E^3 will linearly increase over time with unitary coefficient and initial value $cost(E^3_1) = 1$. Finally, the threshold for the uncertainty index will be set to 0.9.

If the sensory readings at time $t = 1$ are

$$[E^1_1, E^2_1, E^3_1] = [1, 0, 1] \ ,$$

the corresponding belief for the state variable, computed according to Equation 2, will be

$$Bel(X_1) =< 0.906, 0.094 > \ ,$$

meaning that with high probability the user is not present in the monitored area. According to Equation 4, this belief distribution results in an uncertainty equal to $U(X_1) = 0.451$, and the cost index will be $cost(X_1) = 3$. Since the uncertainty index falls below the threshold, the sensor configuration will not be varied for the next step.

We now suppose that at the next time instant sensors produce the readings:

$$[E^1_2, E^2_2, E^3_2] = [2, 1, 1] \ ,$$

possibly associated to the user entering the monitored area; the belief on the state variable will be:

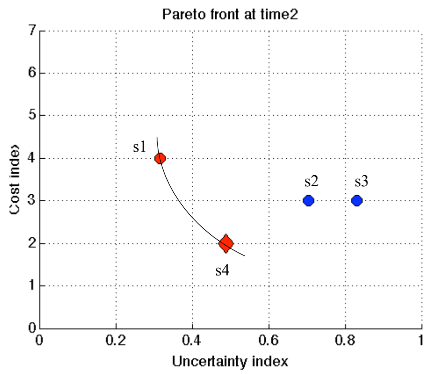
$$Bel(X_2) =< 0.057, 0.943 > \ .$$

Table 1. CPT for state transition: $P(X_t|X_{t-1})$.

		$\mathbf{X_t}$	
		0	**1**
$\mathbf{X_{t-1}}$	**0**	0.8	0.2
	1	0.2	0.8

Table 2. CPTs for sensor models: $P(E^1_t|X_t)$, $P(E^2_t|X_t)$ and $P(E^3_t|X_t)$.

		$\mathbf{E^1_t}$			$\mathbf{E^2_t}$		$\mathbf{E^3_t}$	
		0	**1**	**2**	**0**	**1**	**0**	**1**
$\mathbf{X_t}$	**0**	0.5	0.3	0.2	0.9	0.1	0.6	0.4
	1	0.1	0.1	0.8	0.4	0.6	0.2	0.8



s	U(s)	C(s)
s1=[1,1,1]	0.315	4
s2=[0,1,1]	0.705	3
s3=[1,0,1]	0.830	3
s4=[1,1,0]	0.488	2

Fig. 5. Pareto-dominance analysis of the various configurations of the sensory infrastructure at time $t = 2$. The table on the right shows the indices $U(s)$ and $C(s)$ for the current configuration at time $t = 2$, and for the alternative configurations.

The new sensory readings cause a dramatic change in the belief about user's presence. The uncertainty index will now amount to $U(X_2) = 0.315$, well below the threshold; however, the cost of sensor E^3 has grown up to $cost(E_2^3) = 2$, which results in a corresponding increase in the cost of the probabilistic inference ($cost(X_2) = 4$) not ascribable to additional sensor activations. This condition triggers the re-configuration process.

During re-configuration, the hypothetical uncertainty is checked against the costs of the different sensory conditions obtained by toggling the state of one of the sensors with respect to the current configuration. In our case, the three possible configurations are (E^1, E^2), (E^1, E^3), and (E^2, E^3), corresponding to states $[1, 1, 0]$, $[1, 0, 1]$, and $[0, 1, 1]$ respectively. Indices of uncertainty and cost are computed as explained in Section 3.2, producing the values shown in the table reported in Figure 5.

The Pareto dominance analysis of the different solutions is shown in Figure 5, and allows to identify configurations $s1$, and $s4$ as belonging to the optimal front; the former corresponds to the current configuration, whereas the latter is obtained by de-activating sensors related to evidence node E^3. The solution improving the index that caused the alarm will be chosen within those in the optimal front; in this case, this will correspond to configuration $s4$, which allows to reduce the cost of the BN.

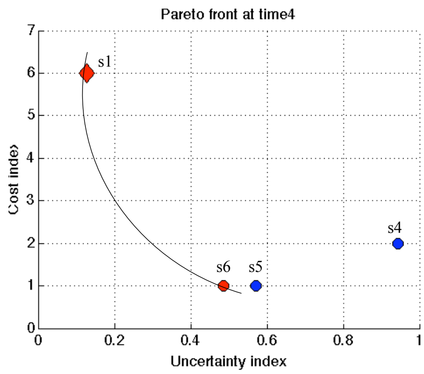
Step $t = 3$ will start with a new configuration where the considered evidence node are E^1 and E^2. Assuming that current sensory readings are

$$[E_3^1, E_3^2] = [2, 1] \ ,$$

the belief for the state variable will be

$$Bel(X_3) = < 0.013, 0.987 > \ ,$$

meaning that the new sensory readings reinforce the belief about the presence of the user. The uncertainty index is equal to $U(X_3) = 0.097$, still below the relative



s	U(s)	C(s)
s4=[1,1,0]	0.944	2
s5=[0,1,0]	0.571	1
s6=[1,0,0]	0.484	1
s1=[1,1,1]	0.125	6

Fig. 6. Pareto-dominance analysis of the various configurations of the sensory infrastructure at time $t = 4$. The table on the right shows the indices $U(s)$ and $C(s)$ for the current configuration at time $t = 4$, and for the alternative configurations.

threshold, and the cost of the sensor relative to E^3 increases up to $cost(E_3^3 = 3)$, which however does not affect the cost of the probabilistic inference ($cost(X_3) = 2$). Since all indices fall below the relative thresholds, the configuration will not vary for the next step.

At time $t = 4$, we assume that the sensory readings are

$$[E_4^1, E_4^2] = [1, 0] \ ;$$

by looking at the CPTs, it is clear that those readings are not the ones with highest probability with respect to the user's presence. This discrepancy produces a change in the belief, which is however coupled with a high uncertainty:

$$Bel(X_4) =< 0.639, 0.361 > ,$$

and $U(X_4) = 0.944$. Since the uncertainty index falls over the threshold, the self-configuration process is triggered again.

The current state is $s = [1, 1, 0]$, so the three possible alternative configurations are $[0, 1, 0]$, $[1, 0, 0]$, and $[1, 1, 1]$, corresponding to activating evidence nodes (E^2), (E^1), or (E^1, E^2, E^3) respectively. Now $cost(E_4^3) = 4$, and the indices of uncertainty and cost are show in the table reported in Figure 6.

A Pareto-dominance analysis of the possible solutions identifies configurations $s1$ and $s6$ as belonging to the optimal front, as shown in Figure 6. Within such front, the solution improving the index that triggered an alarm is chosen, namely, in this case, $s1$ which allows to decrease the uncertainty.

In other words, the sensor associated to evidence node E^3 is re-activated, regardless of the high energy cost, since this is the way for the system to gather the additional information necessary to lower its uncertainty. Such costly re-activations occur when other currently activated sensors provide information not matching with the current belief, due to excessive noise or to an actual variation for the state. In both cases, it is convenient to re-activate a costly sensor just for the time necessary to decrease the system uncertainty about the state of the external world, and then deactivate it again.

5 Conclusions

This paper proposed a Bayesian networks model which includes a meta-level allowing for dynamic reconfiguration of the sensory infrastructure providing the evidence for the probabilistic reasoning. The system has been instantiated on an Ambient Intelligence scenario for the extraction of contextual information from heterogeneous sensory data. The added meta-level accounts both for the accuracy of the outcome of the system, and for the cost of using the sensory infrastructure. The provided realistic example showed that the proposed approach is promising in overcoming the difficulties arising from the inherently imprecision of sensory measurements, allowing to obtain a sufficiently precise outcome, while also minimizing the costs in terms of energy consumption.

Finally, we plan to extend the test set with a real-world scenario, in order to evaluate the scalability with respect to the number and the heterogeneity of data sources, and the sensitiveness to the variability of energy consumption functions, as well as to compare the system performances with other meta-management strategies.

References

1. Akyildiz, I., Su, W., Sankarasubramaniam, Y., Cayirci, E.: A survey on sensor networks. IEEE Communication Magazine 40(8), 102–114 (2002)
2. Bernardin, K., Ekenel, H., Stiefelhagen, R.: Multimodal identity tracking in a smart room. Personal and Ubiquitous Computing 13(1), 25–31 (2009)
3. De Paola, A., Gaglio, S., Lo Re, G., Ortolani, M.: Sensor9k: A testbed for designing and experimenting with WSN-based ambient intelligence applications. Pervasive and Mobile Computing. Elsevier (2011)
4. Deb, K., Agrawal, S., Pratap, A., Meyarivan, T.: A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: Nsga-ii. In: Parallel Problem Solving from Nature PPSN VI. pp. 849–858. Springer (2000)
5. Kasteren, T., Englebienne, G., Kröse, B.: An activity monitoring system for elderly care using generative and discriminative models. Personal and Ubiquitous Computing 14(6), 489–498 (2010)
6. Li, N., Yan, B., Chen, G., Govindaswamy, P., Wang, J.: Design and implementation of a sensor-based wireless camera system for continuous monitoring in assistive environments. Personal and Ubiquitous Computing 14(6), 499–510 (2010)
7. Lu, C., Fu, L., Meng, H., Yu, W., Lee, J., Ha, Y., Jang, M., Sohn, J., Kwon, Y., Ahn, H., et al.: Robust Location-Aware Activity Recognition Using Wireless Sensor Network in an Attentive Home. IEEE Transaction on Automation Science and Engineering 6(4), 598–609 (2009)
8. Pearl, J.: Probabilistic reasoning in intelligent systems: networks of plausible inference. Morgan Kaufmann (1988)
9. Pirttikangas, S., Tobe, Y., Thepvilojanapong, N.: Smart environments for occupancy sensing and services. Handbook of Ambient Intelligence and Smart Environments pp. 1223–1250 (2009)