The design of a Bayesian Network for mobility management in Wireless Sensor Networks

D. Ballari, M.Wachowicz

Centre for Geo-information, Wageningen University, Droevendaalsesteeg 3, 6708 PB Wageningen, The Netherlands
Email: daniela.ballari@wur.nl, monica.wachowicz@wur.nl

1. Introduction

Mobility in Wireless Sensor Networks (WSNs) is achieved by attaching sensors to mobile objects such as animals (Juang et al. 2002), people (Campbell et al. 2008), and robots (Dantu et al. 2005). Currently, the research about WSN management is mainly focused on energy management functions to control how sensors should use their power; fault management functions to solve sensor problems; quality of services (QoS) management functions to quantify and control the performance; and mobility management functions to detect the sensor movement so that the network wireless connectivity is always maintained (Wang et al. 2010; Ruiz et al. 2003). However, the sensor mobility has not only an impact on the network connectivity, but also on the network spatial coverage. In mobile WSNs, the extension of the spatial coverage is often changing, and as a result, the region of interest might be inaccurately sensed by the mobile sensors. Therefore, the representation of a movement context is important to avoid making interpretations and decisions outside of the situation in which the WSN is capturing information; and make possible to decide where, when and how the sensing is performed in order to obtain the most suitable spatial coverage of a region of interest.

This paper proposes a Bayesian network (BN) approach for making explicit the structural and parametric components of a movement context using WSN metadata. The aim is to infer mobility management requirements when a spatial coverage is incorrectly covering a Region of Interest (ROI), regardless the network connectivity. The BN approach provides several advantages regarding to the probabilistic representation of a movement context, the inference of mobility management requirements based on such a context, and the dynamic updating of the movement context every time new metadata are retrieved from the WSN. Previous research works in WSNs have used a similar approach focusing on energy management (Elnahrawy and Nath 2004) and prediction of sensor movement directions (Coles et al. 2009). The main contribution of our work is the analysis of how well a ROI is being covered by mobile sensors, and what are the requirements to improve that coverage given a movement context. A controlled experiment was carried out and the results show that, when the ROI is not being sufficiently covered by a WSN, the BN can probabilistically infer different mobility management requirements, based on a given movement context. Two movement contexts have been used to illustrate this approach. They are related to whether the sensing is being carried out in an emergency situation or not.

2. The Bayesian network approach

Bayesian network is a directed acyclic graph that encodes probabilistic relationships among variables of interest. The graph structure consists of nodes representing variables of interest; each node having a set of mutually exclusive states; and their edges representing relationships among nodes (association, influence or causality).

Moreover, conditional probability tables are provided as parameters to quantify the relationship strengths (Charniak 1991; Jensen and Nielsen 2007; Pearl and Russell 2001). In our approach, the BN nodes are the WSN metadata of interest for inferring the most suitable mobility management requirements according to a movement context. Metadata have been grouped into four categories that illustrate the movement context in which the sensing is carried out. The categories are sensor, network, organizational, and sensing (Ballari et al. 2009). Therefore, a movement context probabilistically represents a set of interrelated metadata used to describe the sensing of a region of interest and the state of a WSN (Table 1).

Table 1. Examples of metadata describing the four categories of a movement context.

Categories of a movement context		Description
Network	**Sensor**	Metadata describe, for instance, the energy level, location, and mobility for each individual sensor forming the WSN.
		Metadata describe, for instance, the state of the WSN as a whole such as spatial coverage, topology or network energy level.
Organizational		Metadata describe, for instance, the purposes and general objectives of the WSN.
Sensing		Metadata describe, for instance, the sensing phenomenon, sensing procedures, and the spatial distribution and variability of mobile sensors within a region of interest.

The conditional probability tables are learned from WSN metadata using the Expectation-Maximization learning algorithm (Dempster et al. 1977). Moreover, probabilistic inference is used to know the most likely state of unobserved nodes, such as the mobility management requirements; and update probabilities in the light of new evidences. The evidences could be new metadata retrieved from the WSN or our own beliefs about the WSN state. Finally, the updated probabilities are propagated throughout the BN based on the edges (i.e. links) among metadata (Jensen and Nielsen 2007).

3. Implementation

We have carried out a controlled experiment using a mobile WSN with five GPS enabled sensors equipped with the Crossbow MTS420 sensor board. The sensors were carried by people in movement, which in turn, has generated different spatial coverages over time. The experiment generated a data set of 1200 observations during a period of one hour.

The BN structure (metadata, states and relationships) was implemented in the Netica software and Figure 1 shows how the BN nodes are related within the four categories of a movement context. In the sensor category, *Energy_Level*, *Congestion*, *Known_location* and *Type_of_Mobility* monitor the sensor mobility, meanwhile the spatial coverage, in the network category, is monitored by the *Spatial Coverage*. In the sensing category, *Coverage_comparison* computes whether the spatial coverage is insufficiently covering a ROI. Finally, *Region_of_Interest* and *Purpose_of_Application* monitor the state of a WSN according to the application domain. Table 2 illustrates the metadata and their respective values that were processed in a PostgreSQL-PostGIS database.

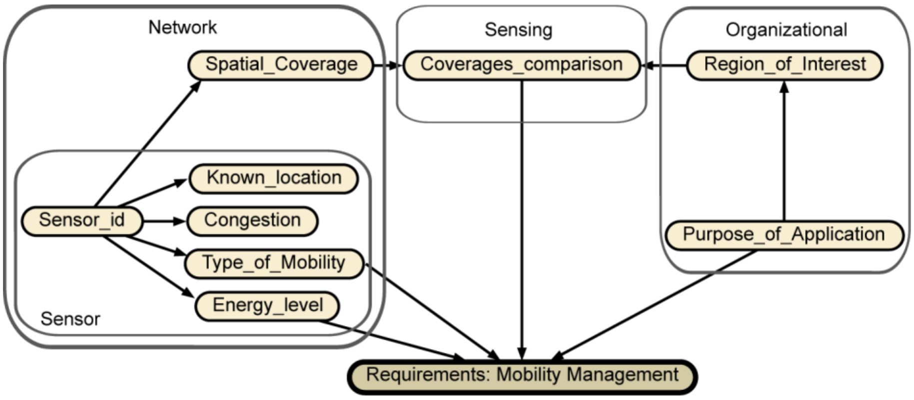

Figure 1. The Bayesian network structure.

Table 2. Overview of the metadata used within the Bayesian network.

Category		Metadata (BN nodes)	Description	Metadata values (states)
Network	**Sensor**	*Sensor id*	Identifier of sensors forming the WSN	Depends on the WSN state
		Known location	Observations that have / not have well-known GPS location	Yes No
		Energy level	Sensors in low / high energy level	Low High
		Congestion	Sensors being overused to disseminate sensing data	True False
		Type of Mobility	Sensors with controlled / uncontrolled mobility	Controlled Uncontrolled
		Spatial Coverage	Identifier of different spatial coverages	Depends on the calculated spatial coverages
Organizational		*Purpose of Application*	Application assigned to the WSN (Environmental monitoring)	Emergency situation Normal situation
		Region of Interest	Optimum and well-defined ROI	Depends on the defined ROI
Sensing		*Coverage comparison*	Comparison between the spatial coverages and the ROI	Enough Not enough

Finally, mobility management requirements can be inferred with the rule showed in Figure 2, based on whether it is more likely to change a sensor location or search for new sensors.

IF → *Coverages_comparison* is *Enough* → THEN → No_requirements

IF → *Coverages_comparison* is *Not_enough*
and *Type_of_Mobility* is *Controlled*
and *Energy_level* is *High*

IF → *Coverages_comparison* is *Not_enough*
and *Type_of_Mobility* is *Controlled*
and *Energy_level* is not *High*
and *Purpose_of_Application* is *Emergency situation*

THEN → Change_sensor_location

ELSE → Search_for_new_sensors

Figure 2: Rule for inferring mobility management requirements

4. Results

4.1 Spatial coverages

We detected 43 spatial coverages, each of them with different boundaries and time periods. Figure 3 illustrates some examples of them.

Figure 3. The computed spatial coverages. (A) The total spatial coverage and (B) four examples of different spatial coverages.

4.2 Movement Context

The overall results of the BN show that the ROI was sufficiently covered by the WSN spatial coverage with a 36.5% of probability. Therefore, any mobility management requirements were inferred. However, in other cases, the ROI was insufficiently covered by the WSN spatial coverage (63.5% probability). Thus the BN inferred the most likely mobility management requirements. The following examples illustrate the BN behavior whether the situation was normal in an environmental monitoring or was an emergency.

Normal situation. Figure 4 shows an example of the movement context in which the ROI was insufficiently covered by the WSN. The BN inferred to search for new sensors as the most likely mobility management requirement, by applying the rule of Figure 2 with the *Purpose_of_Application* as an environmental monitoring under a normal situation and the *Energy_Level* in a very low level (58,3% probability).

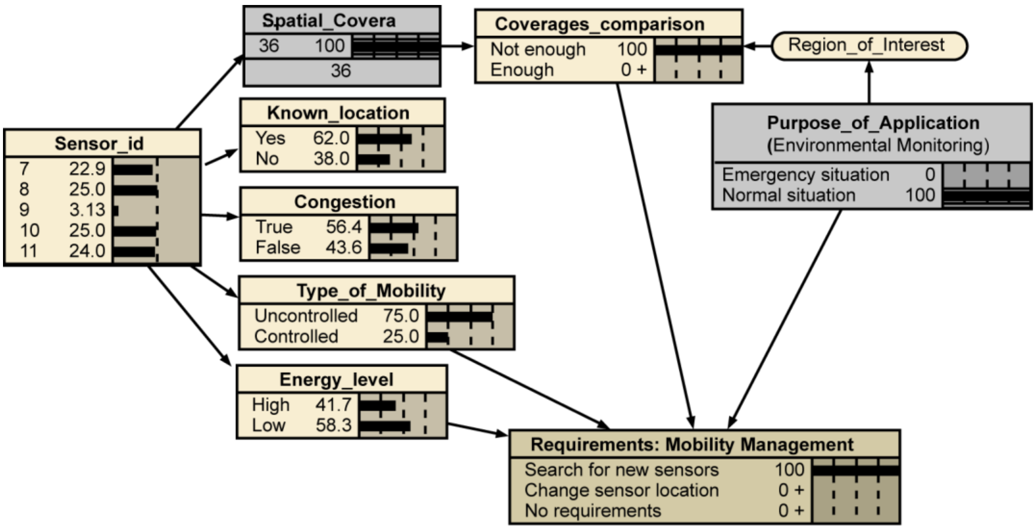

Figure 4. Example of the Bayesian network of the movement context of monitoring in a normal situation.

Emergency situation. What would happen if there was suddenly an emergency? By assigning the maximum probability (100%) to the emergency state in the example of Figure 4, the probabilities were propagated throughout the BN updating the requirements. Figure 5.a shows how the mobility management requirements have changed after the updating. The new requirements were to search for new sensors (75% probability) as well as change the sensor location (25% probability). They were obtained applying the rule of Figure 2 considering that, in the given emergency, the energy level was not longer an important factor in the inference.

Moreover, changing the sensors location can only be performed with sensors with controlled mobility, and the BN allows us to know, in the current movement context, which those sensors are. Thus when assigning the maximum probability (100%) to the controlled *Type_of_Mobility*, the probabilities were propagated to *Sensor_id* by showing the available sensor (Figure 5.b). This also explains the difference in the probabilities for searching for new sensors (75%) and changing sensor location (25%). Both requirements could be performed, however the sensor relocation had less impact (25%) on the improvement of the coverage mainly because there was only one sensor with controlled mobility.

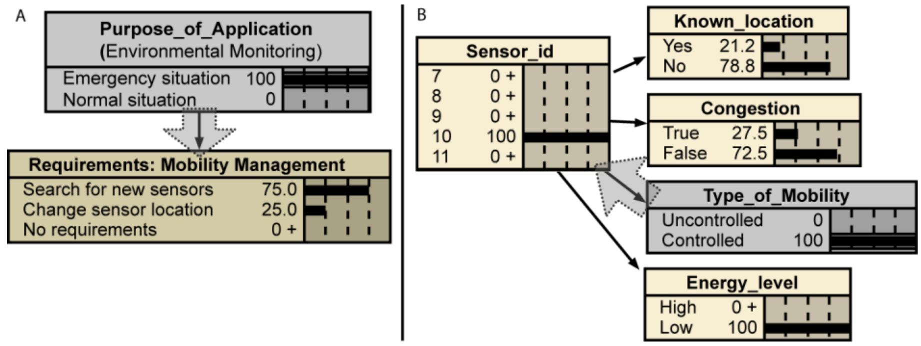

Figure 5. Probabilities propagated throughout the movement context in an emergency situation. (A) The inferred requirements and (B) the available sensor to perform the "change sensor location" requirement.

5. Conclusions

This paper describes how the Bayesian network approach can make explicit the structure and parameters of different movement contexts of a mobile WSN. It also shows how these movement contexts play an important role in the probabilistic inference of mobility management requirements. Two different movement contexts were used to illustrate the environmental monitoring during a normal and an emergency situation. The results show how the requirements have changed according to these movement contexts.

The use of BN has mainly two advantages: a) the graph structure interrelates metadata of the four categories of a movement context and also probabilistically connects those metadata having a direct influence on the mobility management requirements; and b) the probabilistic inference shows which states of a WSN are more likely to occur in each movement context, and as a result, this can allow us to better interpret the requirements.

The implementation has been followed a centralized approach since the computation was carried out at the network level. This approach becomes very difficult that sensors could infer requirements by themselves. Further studies are needed to analyze if some requirements, which do not involve the movement context of the whole WSN, could be taken at sensor level by decentralizing some metadata belonging to the network and organizational categories.

References

Ballari D, Wachowicz M and Manso-Callejo M, 2009, Metadata behind the interoperability of Wireless Sensor Network. *Sensors*, 9(5):3635-3651.

Campbell A, Eisenman S, Lane N, Miluzzo E, Peterson R, Lu H, Zheng X, Musolesi M, Fodor K and Ahn G, 2008, The rise of people-centric sensing. *IEEE Internet Computing*, 412-21.

Charniak E, 1991, Bayesian Networks without Tears. *AI magazine*, 12(4):50-63.

Coles M, Azzi D, Haynes B and Hewitt A, 2009, A Bayesian network approach to a biologically inspired motion strategy for mobile wireless sensor networks. *Ad Hoc Networks*, 7(6):1217-1228.

Dantu K, Rahimi M, Shah H, Babel S, Dhariwal A and Sukhatme Gs, 2005, Robomote: enabling mobility in sensor networks. In: *Proceedings of the 4th international symposium on Information processing in sensor networks*, Los Angeles, California, USA, 404-409.

Dempster A, Laird N and Rubin D, 1977, Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society*, 39(1):1-38.

Elnahrawy E and Nath B, 2004. Context-aware sensors. *Wireless Sensor Networks in Lecture notes in computer science*, Springer, Berlin, 77-93.

Jensen F and Nielsen T, 2007. *Bayesian networks and decision graphs*. 2nd edn., Springer, Berlin.

Juang P, Oki H, Wang Y, Martonosi M, Peh L and Rubenstein D, 2002, Energy-efficient computing for wildlife tracking: Design tradeoffs and early experiences with zebranet. *SIGOPS Operating Systems Review*, 36(5):96-107.

Pearl J and Russell S, 2001, Bayesian networks. *Handbook of brain theory and neural networks*, Published in: MIT Press, Cambridge.

Ruiz L, Nogueira J and Loureiro A, 2003, Manna: A management architecture for wireless sensor networks. *IEEE Communications Magazine*, 41(2):116-125.

Wang Y-C, Wu F-J and Tseng Y-C, 2010, Mobility management algorithms and applications for mobile sensor networks. *Wireless Communications and Mobile Computing*.