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Accepted version

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In Proceedings of the 12th international conference on Artificial intelligence around man and beyond, 2011, pp. 438-444

Probabilistic Anomaly Detection for Wireless Sensor Networks

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Abstract. Wireless Sensor Networks (WSN) are increasingly gaining popularity as a tool for environmental monitoring, however ensuring the reliability of their operation is not trivial, and faulty sensors are not uncommon; moreover, the deployment environment may influence the correct functioning of a sensor node, which might thus be mistakenly classified as damaged. In this paper we propose a probabilistic algorithm to detect a faulty node considering its sensed data, and the surrounding environmental conditions. The algorithm was tested with a real dataset acquired in a work environment, characterized by the presence of actuators that also affect the actual trend of the monitored physical quantities.

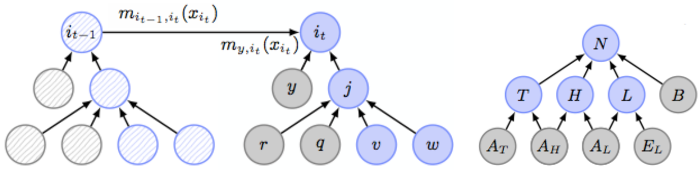
Keywords: Autonomic Computing; Probabilistic Reasoning; Wireless Sensor Networks.

1 Introduction

Wireless Sensor Networks (WSNs) are composed of a set of interconnected devices equipped with sensors for measuring various physical quantities [1] and as such, they may be used in AI systems for acquiring knowledge about an application domain; clearly, it is important that they are not affected by faults. The present work describes a probabilistic approach for the detection of such anomalies in WSN by exploiting statistical information extracted from data gathered by the nodes themselves. The present work extends our previous work [2], and it aims at modeling the overall behavior of a sensor node, as well as the external factors potentially affecting its operations by a Bayesian network, so that belief propagation may be used to infer the overall health status of the node.

2 Related Work

The topic of anomaly detection for WSN has already been addressed in current literature, but many works fail to consider peculiar characteristics that may lead to a wrong anomaly detection. In [3] an approach for identifying regions of faulty sensor nodes is presented, with good performance for large faulty sets, but which focuses only on hardware faults. Our approach is not sensitive to the nature of the faults, and the probability of a correct diagnosis is independent of the amount of nodes. In [4] a method for detecting faulty sensor nodes is presented. The method uses Principal Component Analysis (PCA), and wavelet decomposition for analyzing historical data for small-scale WSNs. The faulty sensor nodes can be detected by extracting high-frequency coefficients of wavelet decomposition, but the presence of actuators is not considered, which may alter the outcome of the proposed algorithm. In [5], the authors address potential errors in sensor measurements due to faults, and develop a distributed Bayesian algorithm for



(a) (b)

Fig. 1. (a) A Bayesian network, highlighting message passing between two showing hidden and observed nodes. (b) The proposed Bayesian network.

detecting and correcting such faults. They present a sample scenario where sensors detect concentrations of some chemical agent may exceed some pre-defined threshold, and propose a Bayesian approach based on the assumption that measurement errors due to faulty equipment are likely to be uncorrelated, whereas environmental measurements are spatially correlated. A similar assumption is used in our work, although our application domain is different, and our approach is applicable to generic off-the-shelf sensors, and takes the specific operational context into account.

3 Detecting Anomalies in Wireless Sensor Nodes

In order to assess the operational good standing of a sensor node we represent its behavior through a Bayesian network (BN) able to model the influence of external factors. The target application domain is an indoor environment; the WSN nodes are supposed to be powered by non renewable energy sources and the user is allowed to influence the environment by operating actuators.

3.1 Modeling Sensor Nodes Behavior

We are interested in modeling the behavior of each sensor node by way of a BN capturing the influence of the surrounding environmental conditions over the sensors on board of the node using the belief propagation (BP) [6] to infer on graphical models expressed by the BN. We refer to the rightmost BN in Figure 1(a) to introduce the theoretical grounds; let S indicate the set of nodes of the BN, with $|S| = s$. Each variable can assume a discrete number of states, and we will indicate one of the different states of node i as x_i. To compute the message between hidden nodes j and i, let H_j and B_j indicate the sets of hidden and observed variables connected to node j; in the depicted case $H_j = \{v, w\}$, and $B_j = \{q, r\}$, with $H_j, B_j \subset S$, at the end the messages are of the form:

$$m_{ji}(x_i) \leftarrow \sum_{b \in B_j} \phi_j(x_j, x_b)\psi_{ji}(x_j, x_i) \cdot \prod_{k \in Ngh(j) \setminus i} m_{kj}(x_j) \tag{1}$$

where $\phi_j(x_j, x_b)$ and $\psi_{ji}(x_j, x_i)$ represent the *potential functions* between pairs of variables of the graphical model. The former controls the relationship between observed and hidden variables, whereas the latter controls the relationship among hidden variables of the graphical model. $Ngh(j)$ represents the set of neighbors of node j. The "belief" x_i assumed by node i is expressed as follows:

$$b_i(x_i) = \frac{1}{z_i}\phi_i(x_i, y_i) \cdot \prod_{k \in Ngh(j)} m_{ki}(x_i) \tag{2}$$

where z_i is a normalization factor. Finally, we consider that the values of the variables in the model may change over time, so the beliefs are actually re-computed for each instant. Figure 1(a) shows the relationship between two instances of the model at consecutive time instants; a message will also be exchanged between two consecutive instances of node i, and represents an estimate of the state node i will assume at time t, computed at time $t-1$.

3.2 Specializing the Model for Indoor Environmental Monitoring

Figure 1(b) shows the structure of the BN we used in our context. Each sensor node is assumed to be equipped with three sensors for measuring light exposure, temperature and relative humidity, respectively, and its operating status is modeled as a binary stochastic variable. Variable N represents the health status of a sensor nodes, and it has to be ultimately inferred; in our model it is influenced by variables L, H, and T which represent the estimators of the operating status of the three on-board sensors. Each of them models the status of the corresponding sensor also taking into account the operating context, which in our case is represented by the surrounding environmental conditions, as well as the potential influence of actuators over the readings of each sensor. Variables E_L, E_H, and E_T represent the raw estimators of the health status of the three sensor with respect to their surrounding environment, and they are computed via the technique described in our previous work [2], that labels a healthy sensor as Good, and a faulty sensor as Damaged. Variables A_L, A_H, and A_T model the influence of the actuators for light, humidity and temperature respectively. The probabilities associated with such variables are computed with respect to the acquired readings; if the actuator is turned on, the probabilities are computed on the fly by applying Gaussian regression that allows to estimate $p(x_N = \text{Good} \,|\, x_{A_T} = \text{On})$. Whenever the actuator is turned off, we assume a uniform distribution for the corresponding variable. Finally, the operating status of a sensor node is also influenced by the charge level of its battery; our model captures it through variable B using an approach based in the correlation computed between a node having low power and one with sufficient power.

3.3 Inferring the Health Status of an Environmental Sensor Node

As previously mentioned, the overall health status of a sensor node is inferred by computing the belief $b_{N(t)}(x_N)$ of the corresponding node N in the BN; in our scenario x_N is a 2-dimensional vector containing the probabilities associated to the two labels, Good and Damaged. As the model evolves over time, it takes on a configuration depending on the acquired measurements as well as on external perturbing factors. Eventually, the belief about x_N at time t will indicate which of the two possible states is the correct inference for the operating status of the sensor node. In our model, variables $E_L, E_H, E_T, A_L, A_H, A_T, B$ are the observed variable, whereas variables N, L, H, T are hidden. The marginal probability of the hidden variable N_t, in particular is estimated via BP, by applying Equation 2, which in the specific case becomes:

$$b_{N(t)}(x_N) = \frac{1}{z_N} \phi_t(x_N, x_B) \cdot \prod_{j \in \{H,L,T,N_{t-1}\}} m_{jN}(x_N) \tag{3}$$

where $\phi_t(x_N, x_B)$ is the probability $P(N|B)$, whereas messages are computed by Equation 1. As shown in Equation 3, the state of node N at time t requires a message from node N_{t-1}; we assume that such message is null for N_0.

4 Experimental Results

In order to assess the performance of our method we set up a typical work environment, and we deployed 5 sensor nodes. The setting also included an actuator that influences temperature and humidity, and an artificial lighting. For our experiments, we collected a dataset acquired during the period ranging from March, 24th to April, 14th 2011. The sampling period of each node is 3 minutes; each of the following test scenarios considered an overall time span of 24 hours. Due to its central location, node 5 has been specifically considered as representative for the evaluation of the performance of the proposed algorithm; as will be shown, the influence of all kinds of actuators is more noticeable as compared to the remaining nodes. Three sample scenarios are presented follow to better explain the performance of our approach. The performance of the proposed approach was quantified by computing two metrics: the *accuracy*, measuring the reliability of the classifier with respect to the detection of Good and Damaged nodes, and the *precision*, which specifically considers the detection of faulty node; they are computed as follows:

$$Ac = \frac{Tn + Tp}{Tp + Fn + Fp + Tn} \quad (4) \qquad Pr = \frac{Tp}{Tp + Fp} \quad (5)$$

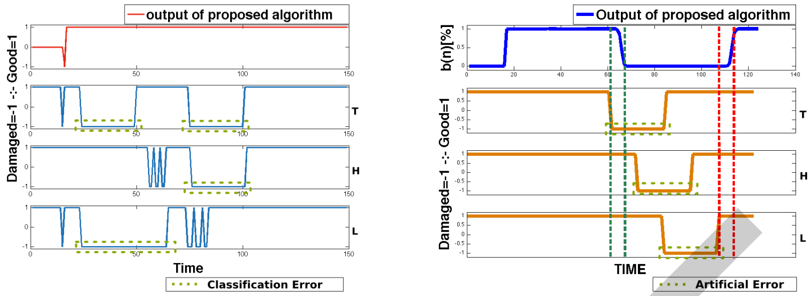
where Tp measures the amount of nodes whose health status is Good and are actually detected as such (i.e. true positives), Fp measures the amount of nodes whose health status is Good, but are erroneously detected as Damaged (i.e. false positives), and analogously for the two remaining parameters.

4.1 Scenario 1: Dataset influenced by actuators

In this scenario, the BN processes data influenced solely by the action of the actuators, it identifies data where such influence is relevant, and succeeds in classifying the relative sensors as healthy, even when the underlying MRF-based classifier would trigger an alarm.Our BN-based classifier provides better performance thanks to the additional information extracted from the environmental context, like that the actuators are turned-on. The outcome of the proposed algorithm is shown in the topmost plot of Figure 2(a); the three other plots in the same Figure show the status of the individual sensors for humidity, temperature, and light as computed by the MRF-based algorithm. The reported plots specifically consider node 5. Figure 2(a) highlights that the proposed algorithm outperforms the basic MRF-based classifier. The performance of this scenario is reported in the first row of Table 1.

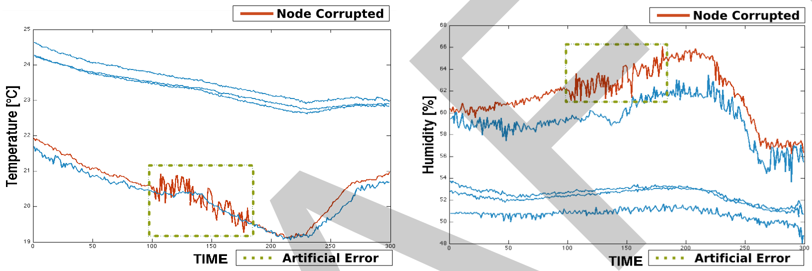
4.2 Scenario 2: Dataset influenced by a simulated fault

In this scenario, the dataset corrupted by an artificial error only is processed. Figure 3 shows the original dataset; the dotted rectangle highlights the presence of errors. In this case the accuracy value for the proposed algorithm is lower than the classifier based on the MRF, due to a transition phase necessary for



(a) (b)

Fig. 2. (a) Environmental information accounted in the Bayesian classifier, the errors of classification are committed by the classifiers MRF based; (b) Progress of belief of the node 5 during the errors occurred in its sensors, the last three charts indicate the period which the error occur respectively on the sensor of temperature, humidity, and light.



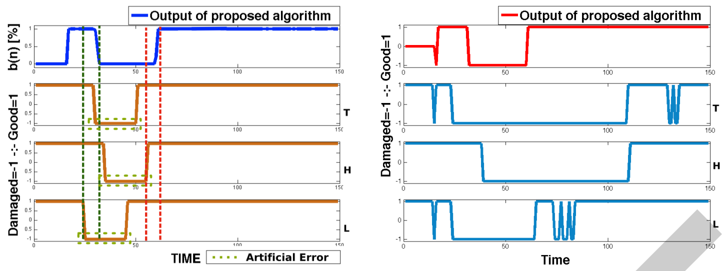
(a) (b)

Fig. 3. (a) Real dataset perturbed by a Gaussian error: (a): temperature; (b): humidity.

the algorithm to converge on the exact state. In the first plot of Figure 2(b), the evolution of the belief about state Good for node 5 is shown. In the others plots, the dotted rectangle surrounds the interval containing the errors for the sensors, which are thus regarded as Damaged. The transition is due to the fact that the network is time dependent, so that the previous state of a node influences the estimation of next value (through message passing). Just for this scenario the performance is shown in the second row of the Table 1.

4.3 Scenario 3: Dataset influenced by actuators and a simulated error

In this scenario, the dataset used is influenced by the action of the actuators, and by an artificial error. As in the first scenario, classifier accounts for the environmental information in its reasoning, and correctly identifies the action of the actuators, but similarly to the second scenario, it singles out the artificial error. The first plot in Figure 4(a) shows the evolution of the belief when the artificial errors occurred on the sensors, and that the belief of the node decreases only in the proximity of errors, so that the status of the node switching toward Damaged value as shown in the first plot of Figure 4(b). The other plots of Figure 4(b) show that the MRF-based classifier approximately identifies the



(a) (b)

Fig. 4. (a) Real dataset of humidity perturbed by the air conditioner and by a fault. (b) Dynamics of the estimate of the status for the classifiers in scenario 3.

Table 1. Performance summary of the experimental scenarios.

	BN Classifier		**MRF-based Classifiers**					
			T		H		L	
	Ac[%]	Pr[%]	Ac[%]	Pr[%]	Ac[%]	Pr[%]	Ac[%]	Pr[%]
Scenario 1	89	90	77	78	63	64	63	63
Scenario 2	70	93	88	99	78	87	–	–
Scenario 3	78	78	52	51	50	42	80	77

faulty sensor, signaling the error for a longer time than the Bayesian classifier, which detects the error upon its occurrence. On the third row of Table 1, the performance of both kind of classifiers are presented for this scenario.

5 Conclusion

In this paper we proposed a Bayesian classifier for the health status of sensor nodes for environmental monitoring considering the external factors that surrounding a node, like actuators. A possible future use of the our work might be in a wider and more complex architecture, such as an autonomic system.

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