A Noise Resilient Distributed Inference Framework for Body Sensor Networks

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Abstract. This paper introduces a distributed Bayesian framework for noise resilient context sensing for Body Sensor Networks (BSNs). By utilizing the causal/dependence structure of the Bayesian network and the introduction of hidden nodes, the inference processes can be distributed to local clusters with added benefit of noise resilience. Issues related to automatic network construction based on backward propagation for parameter learning and noise sensitivity/detection are discussed.

1 Introduction

With recent advances in low power wireless sensing technologies, the concept of Body Sensor Network (BSN) has shown significant strength in continuous monitoring of patients under their natural physiological status [1]. Due to the diversity of the environment and physiological conditions they may experience, understanding of the context within which the signals are collected plays an important role for the accurate prediction of adverse events. Reliable detection of patient activity, however, requires the use of a large number of context sensors around the body. This can potentially introduce a significant burden to the power consumption and bandwidth utilisation. Directly sending all the sensory data to the centralised processing unit requires extensive transmission power and a high bandwidth at the central processing unit. Reducing the transmission range and required bandwidth will greatly reduce the power consumption and prolong the life span of the sensors. Clustering data transmission among neighbourhood can also alleviate the problem of data collision.

Existing research has shown that inferencing with message-passing is potentially useful for distributed sensing systems. However, resilience to communication error and node failures is major obstacle to overcome. Paskin *et al.* proposed a robust message passing algorithm for reasoning in a junction tree model [2] . By converting a standard multiply connected Bayesian Network (BN) into a cluster tree and combining nodes into a clique, the problem of non-convergence and incorrect update of the posterior probabilities due to the loopy feedback in a multiply connected model can be avoided. Furthermore, existing research in BSN has also highlighted need for built-in redundancies in the sensor network for dealing with motion artefact and node failures. The purpose of this paper is to propose a Bayesian framework that permits distributed inferencing with a high level of noise tolerance.

2. Model Description

The main idea of introducing noise resilience to the sensing architecture is the introduction of hidden nodes to a traditional BN. This allows the transformation of a multiply connected network into a singly connected network. Pearson's correlation coefficient was chosen as the dependency measure between a variable pair and complete-link clustering is used to form clusters of correlated child nodes. Unlike ordinary BNs where the conditional probabilities in the link matrices are obtained from the data distribution, the close-form representation for deriving link matrices is not possible for a network with hidden nodes. A backward propagation method used for parameter learning. To assess the overall performance of the proposed method, an ETH reference dataset was used. This consisted of sensor data obtained from accelerometers in performing eight different activities [3]. After extracting the temporal features from the dataset, reference data is constructed by selecting six representative features and two highly correlated features. From the reference data set, a BN is obtained by learning the structure from the training dataset, and hidden nodes were inserted to represent the dependency among correlated children [4], as shown in Fig.1.

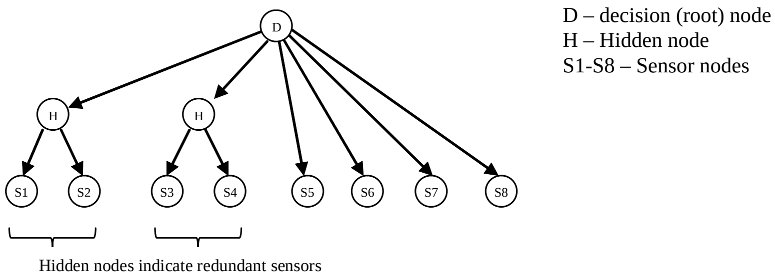

Fig. 1. The structure of the BN with hidden nodes learned from the training dataset.

3. Noise Resilience

To assess the noise resilience of the model, both Gaussian and white noises were introduced to nodes with redundant features. Gaussian noise was generated from a normal distribution with zero mean and the standard deviations (SD) of ¼, ½, and 1 of the SD of the corresponding feature in the original dataset. Fig. 2 and Fig. 3 demonstrates the performance comparison of a naïve BN, and a BN with hidden nodes, and a BN with hidden nodes after re-training with single and dual channel noise interference, respectively. The re-training was performed by using a leaky integrator to update the link matrices with a continuously re-sampled training dataset stored in a FIFO buffer. It is evident that the BNs with hidden nodes outperform the naïve BNs as the noise level increases. The graphs have shown that the insertion of hidden nodes could effectively filter out the noise and maintain the model accuracy. The online updates of the link matrix can further increase the model accuracy.

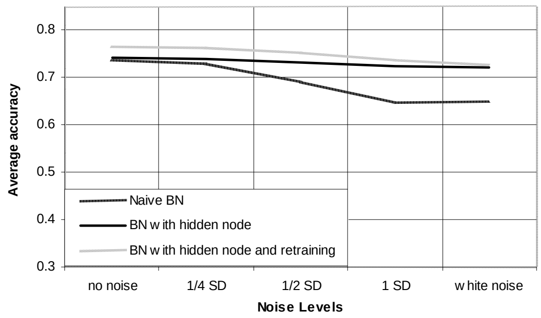

Fig. 2. Performance comparison of different BN models vs. different noise levels in the data received from a redundant sensor

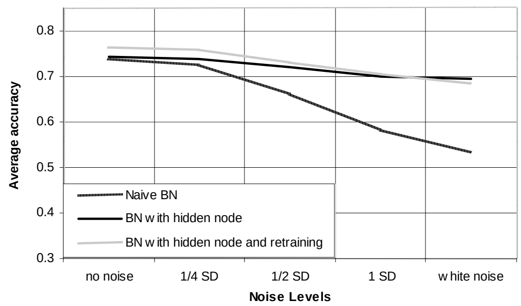

Fig. 3. Performance comparison of different BN models vs. different noise levels in the data received from two redundant sensors.

4. Noise Detection

The hidden node introduced in this paper is to neutralise the effect of the redundant nodes in the network and improve the noise tolerance. In practice, it is also important to isolate, rather than filter out, faulty sensor responses. To this end, the framework described above provides a convenient way of performing sensor noise detection. Since the standard deviation of a static signal is zero, any measurement which involves division by the standard deviation cannot be computed. In this paper, we have used the L1 dependency measure for this purpose, i.e.,

$$\mathrm{Dep}(A,B)=\sum_{AxB}\left|P(a_i \,\&\, b_j)-P(a_i)P(b_j)\right| \quad (1)$$

For online detection of noise in a subnet, the joint probabilities $P(a_i\&b_j)$ and the prior probabilities $P(a_i)$ and $P(b_j)$ are calculated from the data within a shifted window for each pair of nodes in the subnet. Since a hidden node is inserted based on the dependency between the child nodes, the difference between the child-parent dependency should be low if their dependency is maintained. In this case, relatively high difference in child-parent dependency indicates noise interference. The result shown in Fig 4. illustrates the comparison between the difference in child-parent dependency before and after Gaussian noise (with 1SD) was introduced into the subnet. The probabilities are calculated at each time step by using a shifted time window size of 30.

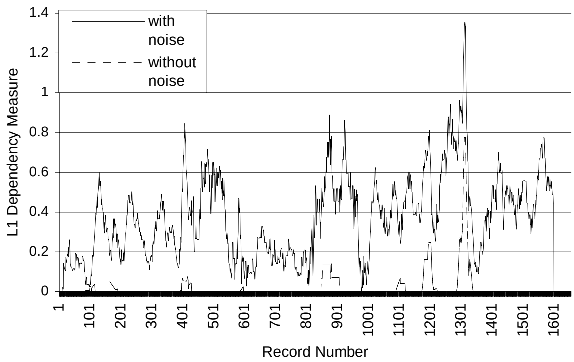

Fig. 4. Comparison of the difference in L1 dependency measure before and after the Gaussian noise is introduced.

5. References

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