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# Estimation Method Based on Deep Neural Network for Consecutively Missing Sensor Data[1]

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**Abstract**—The phenomenon of missing sensor data is very common in wireless sensor networks (WSN). It has a dramatic effect on the usability, stability and efficiency of the WSN-based applications. There exist many methods for the missing sensor data estimation. However, the accurate and efficient consequent estimation of missing sensor data remains a challenging problem. To solve this problem, we propose a new method named consecutive sensor data deep neural network (CSDNN). In this method, firstly, we analyze the correlation coefficients among different types of sensor data and choose a certain number of nearest neighbors of the target sensor nodes. Secondly, to estimate a certain type of sensor data from a target sensor node, we utilize the different types of sensor data that are from the same target sensor node and have strong correlation with the missing ones, and the same type of sensor data from the aforementioned nearest neighbors. We treat these data as the input of the deep neural networks (DNN). Thirdly, we construct the DNN model, discuss the optimized DNN structure for the missing data problem, and test the accuracy of CSDNN for different types of environmental sensor data. The results show that the CSDNN method allows to accurately estimate the consecutively missing sensor data.

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## 1. INTRODUCTION

Wireless sensor networks (WSN) are very popular in different areas and a lot of related problems such as positioning system [1], energy saving methods [2], data coding and optimal transmission path [3], quality of service [4], moving radio sources tracking [5], etc. have become hot research topics.

The applications that are based on the wireless sensor networks collect variety of data from remote sensors. But harsh environments or limited sensor energy always cause sensor data missing phenomenon. Sometimes, consecutive data missing events may happen because of the exhausted sensor nodes. The applications that provide useful information for users through analyzing the collected sensor data will be out of work under the conditions of incomplete sensor data. Therefore, estimate and interpolate the missing sensor data is an essential work for these kinds of applications.

To solve this problem a lot of methods have been proposed. At beginning, resending the missing sensor data acted as a solution for this problem. However, this method can not be used if a sensor is out of energy or broken, it also reduces the efficiency of real-time applications. Therefore, it is a better choice to estimate the missing sensor data. We classify current sensor data estimation solutions into three major categories based on the key algorithms used in these methods.

The first category includes methods that are based on the temporal and spatial relationships among sensor data, the regression model, time series analysis model or both of them to estimate missing values. For example, Mishra et al. [6] treated the rainfall data as time series data and used the artificial neural network to do rainfall prediction. Zhang et al. [7] used multiple linear regression model to estimate missing sensor data. Pan et al. [8] utilized both temporal and spatial connections among sensor data and designed an algorithm called CIAM which used cubic spline interpolation model and multiple regression model. Alippi et al. [9]

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