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A New Missing Values Estimation Algorithm in Wireless Sensor Networks Based on Convolution

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Abstract: Nowadays, with the rapid development of Internet of Things (IoT) applications, data missing phenomenon becomes very common in wireless sensor networks. This problem can greatly and directly threaten the stability and usability of the Internet of things applications which are constructed based on wireless sensor networks. How to estimate the missing value has attracted wide interest, and some solutions have been proposed. Different with the previous works, in this paper, we proposed a new convolution based missing value estimation algorithm. The convolution theory, which is usually used in the area of signal and image processing, can also be a practical and efficient way to estimate the missing sensor data. The results show that the proposed algorithm in this paper is practical and effective, and can estimate the missing value accurately. *Copyright* © 2013 IFSA.

Keywords: Internet of Things, Wireless sensor network, Sensor data, Missing value estimation, Convolution.

1. Introduction

Nowadays, various applications of Internet of Things (IoT) are increasingly developed. But the data missing problem, which is very common in wireless sensor networks, does harm to the feasibility and stability of these IoT application systems. To solve this problem, some methods have been proposed.

In statistics area, the problem of estimating missing values has been investigated and various methods have been used, for example, Mean Substitution, Imputation by Regression, Hot/Cold deck Imputation, Expectation Maximization, Multiple Imputations and so on[1]. But these methods can not apply to the wireless sensor network environment.

Madden[2] proposed a system, named TinyDB, which can query information form the wireless sensor network. In this system, the missed sensor values are estimated by the average of the values of all the other sensors. This method does not consider the corrections

between sensors and estimation results are not accuracy. But it is very simple and it is suitable for the real-time environment.

A Markov chain based missing sensor value estimation method is proposed in [3]. In this method, there are two phases: firstly data traces collected from the deployed sensor networks are analyzed, and then density estimation based procedure are used to derive semi Markov models that capture the patterns and statistics of missing and faulty data in the analyzed sensor data streams.

Association rule mining method is used to estimate the missing values in many papers. Halatchev et al. [4] proposed a power-aware missing values estimation technique, called Window Association Rule Ming (WARM). In WARM, the missing value is estimated by association rule mining method which uses the values available at the sensors related to the target sensor through association rule mining. Specially, for the case when a missing value cannot be estimated by

association value, it is estimated by the average of all available readings for the sensor with the missing value. In the further work, Jiang et al [5, 6] present a data imputation technique based on association rules derived from closed frequent item sets generated by sensors. In [6], the proposed CARM approach can estimate missing sensor value online. In order to find out a data estimation approach which can be applied to the context of data streams, Gruenwald et al. [1] proposed a data estimation technique, named freshness association rule mining (FARM), which uses association rule mining to discover intrinsic relationships among sensors and incorporate them into the data estimation. Wang et al. [7] proposed an imputation technique for context data missing. In [7], association rule mining methods are utilized to perform spatiality and time series analysis on sensor data, and then strong association rules can be generated to interpolate missing data.

To deal with the problem that the locations of the censors are usually inconsistent with the application requirements, Zhang et al. [8] proposed a estimation method which can predict the field values at arbitrary locations by introducing the concepts of interconnection matrices and derive real-time field estimation algorithms.

Umer et al. [9] take a distributed Kriging based method to interpolate a spatial phenomenon inside a coverage hole using available nodal data. In [10], a KNN imputation procedure, which uses a feature-weighted distance metric based on mutual information, is proposed. This method can be used to solve the classification task.

A multiple regression model based missing values imputation algorithm is proposed In [11]. In the further work [12], a temporal correlation based missing values imputation algorithm which adopt linear interpolation model and a spatial correlation based missing values imputation algorithm which adopts multiple regression model are proposed. Based on these two algorithms, an adaptive temporal and spatial correlation based missing values imputation algorithm is proposed.

Convolution theory is typically used in image processing area. Base on traditional convolution algorithm, a normalized convolution method is proposed in [13]. Qin et al. [14] improved this normalized convolution algorithm and proposed a new image in painting algorithm and the experiment results show that their algorithm can deal with the continuous image data losing problems and can get a good performance.

In order to design a feasible and effective missing sensor value estimation algorithm which can estimate missing values with good accuracy and with good performance, in this paper we introduce convolution theory into the field of wireless sensor network and improve it to solve the problem of missing values. Different with previous work, the convolution based solution can be suitable for various missing value conditions and various environmental variables

through choosing appropriate convolution kernel functions.

The remainder of this paper is organized as follows. In section II, we describe the convolution theory and propose the convolution based missing values estimation algorithm. In section III, we will test the algorithm on the sensor data set collected by Intel Berkeley Research Lab and analyze the results. We conclude and expand our future work in section IV.

2. Convolution Based Estimation Algorithm

2.1. Convolution Theory

In mathematics and, in particular, functional analysis, convolution is a mathematics operation on two functions f and g, producing a third function that is typically viewed as a modified version of one of the original functions. It has applications that include probability, statistics, computer vision, and image and signal processing et al.

$$F(t) = \int_{-\infty}^{+\infty} \varphi(\tau) \psi(t - \tau) d\tau \tag{1}$$

Equation (1) is the convolution equation which is used as early as in 1903. In the field of computer science, the discrete form of the convolution is typically used as show in (2).

$$F(t) = \sum_{i=0}^{N} \varphi(i) \bullet \psi(t-i)$$
 (2)

In the image processing area, convolution is typically used for image smoothing and it can be regarded as the operation of sum the weighed pixel value. That means a pixel can be determined by its neighbors and the near neighbor should have high effectiveness to the pixel. In (2), $\varphi(i)$ denotes the grey value of pixel i, and $\psi(t-i)$ denotes the weight of pixel i. If pixel i has N neighbors, the grey value of pixel i can be determined by the average weighted grey values of its neighbors and the target sensor itself, which is the principle of the image smoothing operation.

In the process of image smoothing, the function of $\psi(t-i)$, which is called convolution kernel, is critically important to the results of smoothing operation. In this way, the grey value of a target pixel is affected by both the pixel itself and its neighbor pixels and the kernel function determine how this effect works.

Our approach is based on the idea that the missing data in wireless sensor network can also be estimated by a weighted average of its neighbors. But because the target sensor's value is missing and the value of some of its neighbor sensors may also miss, we can not just use convolution the way as in image smoothing operation. We should improve the conventional method to handle this data missing problem in the wireless sensor network environment. In this paper we define the weight of the missing data sensor is zero, which means the target sensor's data are totally determined by its neighbors and the weight value of each available neighbors is normalized. The algorithm we proposed will be described in detail in section 2.2.

2.2. Convolution Based Missing Values Estimation Algorithm

We proposed a convolution based algorithm to estimate missing sensor data.

The set of all the sensors is denoted as I, and the set of the missing data sensors is denoted as F. I-F represents the set of ordinary sensors. Usually, the number of elements in the set of F is more than one. s_i denotes a sensor in I and then s_i is the missing data sensor which is an element of set F. We estimate the missing data of s_i through its neighbor sensors located in a circle area, of which s_i is the center and r is represented the radius of this circle. The value of r should be assigned in advance, which is greatly related to the accuracy of estimation algorithm. The number of S_i 's neighbor sensors located within the circle with a radius r is denoted as N_i . If r is too small, we have not enough neighbor sensors to estimate the missing value, while if r is too large, the irrelevant sensors are taken into consideration and the accuracy can also be reduced. So, finding an appropriate r is critically important to the estimation accuracy.

Because there are may sensors with missing value, the principle of setting the estimation order is as follows: assuming a given r, the sensor with a higher value of N_i should be estimated earlier. If two sensors have the same value of N_i , the senor with a shorter neighbors' total distance has the priority. With this method, the data of sensors with more neighbors' information are estimated first.

We introduce a variable denoted as $c(s_i)$, which represents the contribution of sensor s_i to estimating the missing data.

$$c(s_i) = \begin{cases} 0 & s_i \text{ miss sensor data} \\ 1 & s_i \text{ has real sensor data} \end{cases}$$
 (3)

In (3), If s_i is a sensor with a real data, its contribution is 1, while if s_i is a sensor which missed sensor value, its contribution is 0.

The estimation value of sensor s_i can be calculated through (4):

$$e(s_i) = \{a \otimes c\}^{-1} \bullet \{a \otimes c \bullet v\} \tag{4}$$

In (4), \otimes means the convolution operator, and \bullet means the multiplication operator. Let v denote the values of neighbor sensors and the value of parameter c can be calculated according to (3).

Let $a(n_i)$ denote the weight of the value of a neighbor sensor n_i (i=1,2...N). Let d_i denote the distance between n_i and s_i , and thus the value of $a(n_i)$ can be calculated by (5).

$$a(n_i) = (\frac{1}{d_i})^2 / \sum_{i=1}^{N} (\frac{1}{d_i})^2$$
 (5)

In (5), the weight of a neighbor sensor n_i is inversely proportional to the square of the distance d_i . In fact, equation (5) is the convolution kernel function. In practical we also use another kernel function (6). In (6) the weight of a neighbor sensor n_i is inversely proportional to the distance d_i .

$$a(n_i) = (\frac{1}{d_i}) / \sum_{i=1}^{N} (\frac{1}{d_i})$$
 (6)

Now in (4), the parameters v, c and a are calculated, so the missing data of s_i can be figured out

It may be worth mentioning that if all contribution values c are equal to 1, equation (3) is reduced to standard convolution:

$$s_{i}^{'} = \{a \otimes c\}^{-1} \bullet \{a \otimes c \bullet v\} = \frac{\{a \otimes 1 \bullet v\}}{\{a \otimes 1\}}$$
$$= \frac{\{a \otimes v\}}{\{a \otimes 1\}} = \{a' \otimes v\}$$
 (7)

In (7), a' represents the normalized weight value.

3. Experiments and Results Analysis

3.1. Sensor Data Set

We use the data set[15] collected by Intel Berkeley Research Lab to test our algorithm. These data collected from the 54 Mica2 sensors deployed in the lab in 36 days. These sensors with weather boards collected time stamped topology information, along with humidity, temperature, light and voltage values once every 31 seconds.

The schema of the sensor data set is show in Fig. 1. Epoch is a monotonically increasing sequence number from each mote. Two readings from the same epoch number were produced from different motes at the same time[15].

3.2. Experiments and Results Analysis

We take epoch 601 which happened in 2004-02-28 for the example to show how our proposed algorithm works. Fig. 2 illustrates the sensors which have values in this epoch. From Fig. 2 we can see that about thirty four sensors having values and specially the sensor of number 28 missed its light value. We take senor 1 as the target sensor to estimate its missing values.

Firstly, according to the coordinates of every sensor which can also be found in the data records[15], we calculate the distance between sensor 1 and the other 54 sensors except sensor 55 because the working period of sensor 55 is different with the others. Thus we get the value of d_i (i= 2, 3....54) in equation (5). Then we sort this series of data (d_i) in ascending order.

Thirdly, based on the distance we choose the neighbor sensors to estimate the missing values. How many neighbor sensors and what kind of sensors should be chosen is the key issue in this stage. In practical, we solve this problem through experiments analysis and we found the number of neighbors could not be too less or too much.

date	time	epoch	moteid	temperature	humidity	light	voltage
уууу- mm-dd	hh:mm: ss.xxx	int	int	real	real	real	real

Fig. 1. The schema of data records.

```
2004-02-28 05:58:17.499256 601 2
                                          39.9591 121.44 2.65143
                                  18.097
2004-02-28 05:58:17.384015 601 3
                                  17.803
                                          39.3483 46.92
                                                         2.66332
2004-02-28 05:58:17.104287 601 7
                                  17.9598
                                          39.0763 97.52
                                                         2.67532
2004-02-28 05:58:16.62355
                           601 9
                                  17.4992 41.1751
                                                  101.2
                                                         2.74963
2004-02-28 05:58:16.359969 601 10 17.4404 41.3435
                                                  53.36
                                                         2.67532
2004-02-28 05:58:17.223756 601
                               11 15.9116 45.3083 2.3
                                                          2.54901
2004-02-28 05:58:16.317312 601
                               13 16.0586 45.0442
                                                  1.38
                                                          2.63964
2004-02-28 05:58:16.897244 601
                               14 15.4902 44.4157
                                                          2.66332
                           601 18 16.6858 40.7706
2004-02-28 05:58:17.28612
                                                  2.76
                                                          2.47467
2004-02-28 05:58:16.984736 601 19 16.6662 40.973
                                                  39.56
                                                         2.65143
2004-02-28 05:58:17.184007 601 20 16.9896 41.5789
                                                  150.88
                                                         3.09333
2004-02-28 05:58:16.835052 601 21 17.0092 39.7896
                                                  93.84
                                                         2.67532
2004-02-28 05:58:17.364506 601 22 16.6466 40.399
                                                  75.44
                                                         2.63964
2004-02-28 05:58:17.166684 601 23 17.4894 38.872
                                                  217.12
                                                         2.66332
2004-02-28 05:58:16.523986 601
                               24 16.7544 40.2976
                                                  136.16 2.67532
2004-02-28 05:58:16.670499 601 25 16.4996 41.3771 97.52
2004-02-28 05:58:17.371817 601 26 16.48
                                          43.1191 114.08
                                                         2.65143
2004-02-28 05:58:16.465968 601 28 16.2644 43.3858
                                                          2.76242
2004-02-28 05:58:16.954066 601 29 17.166 40.4328 172.96 2.66332
2004-02-28 05:58:16.5482
                           601 31 17.0288 41.8476
                                                  136.16 2.65143
2004-02-28 05:58:17.0059
                           601 32 16.9504 41.2425
                                                  108.56
                                                         2.66332
2004-02-28 05:58:16.784032 601
                               33 17.4796 39.7217
                                                  97.52
                                                         2.67532
2004-02-28 05:58:17.446705 601 37 17.95
                                          42.183
                                                         2.67532
2004-02-28 05:58:17.491776 601 40 17.1072 40.8381
                                                  165.6
2004-02-28 05:58:16.898482 601 42 16.3036 42.183
                                                  441.6
                                                         2.65143
2004-02-28 05:58:17.236973 601 43 17.2248 39.5521
                                                  426.88 2.65143
2004-02-28 05:58:17.639729 601 44 16.0096 42.7185
                                                  93.84
                                                         2.65143
2004-02-28 05:58:16.567917 601 46 16.5486 41.0067
                                                  108.56
                                                         2.47467
2004-02-28 05:58:16.961059 601 47 16.3134 42.5847 625.6
                                                         2.65143
2004-02-28 05:58:16.439913 601 48 16.2644 41.8812 108.56 2.68742
2004-02-28 05:58:16.659858 601 50 15.0982 45.1763 75.44
2004-02-28 05:58:17.058265 601 51 16.0488 42.25
                                                  136.16 2.65143
2004-02-28 05:58:16.961496 601 52 15.9116 43.2525 53.36
                                                         2.62796
2004-02-28 05:58:17.304206 601 54 14.1182 48.8704 0.46
                                                         2.62796
```

Fig. 2. Sensor Data in epoch 601.

At last, after have chosen the neighbors of target sensor, we calculate the value of $a(n_i)$ according to equation (5) and equation (6) respectively. In equation (4), parameter ν represents the sensor values of these neighbor sensors and c represents the contribution value of these sensors which can also calculated by

equation (3). Consequently, through the equation (4) we can get the missing values of sensor 1.

Fig. 3 illustrates the estimation missing value of temperature in sensor 1 through different number of neighbors. In this case, the convolution kernel function we chosen is equation (5). From Fig. 3 we can find the estimation value is changing with the

number of the chosen neighbor sensors. Too many or too less neighbors can not lead to an accuracy result. But how can we judge whether an estimated value is accurate or not under the condition that we do not even know the real value? In this case, we take the target sensor's values in previous and continuous epochs as its real value, because we regard that a sensor's value can not change a lot in a very short time.

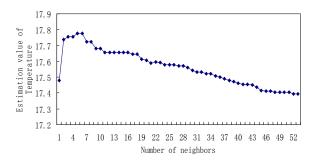


Fig. 3. The estimation value of temperature with convolution kernel function (5).

From Fig. 4 we can find the previous and continuous value of sensor 1, especially the nearest two epochs 600 and 602, in which the sensor values can be regarded as the real value. According to the data schema showed in Fig. 1, we can get the temperature value of sensor 1 is 17.705 in epoch 600 and 17.6952 in 602. According to Fig. 3, choosing 8 (9) or 10 neighbors is appropriate and the estimation values are 17.72173 and 17.68045 respectively. In fact when we choose 8 or 9 nearest neighbors, there only 6 neighbors work because of 3 of them missed values in this epoch. In Fig. 3, we can also find that sometimes, the estimation value does not change even if we add more neighbors. It is because that these new adding neighbors also missed values.

```
2004-02-28 05:54:47.287403 594 1 17.7148 39.2123 43.24 2.67532
2004-02-28 05:55:17.113072
                           595 1 17.6952 39.2463 43.24 2.67532
2004-02-28 05:55:46.759724
                           596 1 17.6952 39.2123 43.24 2.67532
2004-02-28 05:56:16.598863
                           597 1 17.6854 39.2123 43.24 2.67532
2004-02-28 05:57:47.117281
                           600 1 17,705
                                         39.1783 43.24 2.67532
2004-02-28 05:58:47.16005
                           602 1 17.6952 39.1783 43.24 2.68742
2004-02-28 05:59:46.96347
                           604 1 17.6952 39.1783 43.24 2.67532
2004-02-28 06:01:16.399479
                           607 1 17.6952 39.1443 43.24 2.67532
2004-02-28 06:03:17.064269 611 1 17.6952 39.1443 43.24 2.67532
2004-02-28 06:03:46.715768 612 1 17.6854 39.1443 43.24 2.67532
```

Fig. 4. The real data of sensor 1 around epoch 601.

Fig. 5 shows the estimation value of sensor 1 under a different convolution kernel function (5). In this case, the plot of estimation value is very similar with Fig. 4. But the estimation with 8 or 9 neighbors is 17.70671, which is very close to the real value according to Fig. 5.

Fig. 6 illustrates the estimation value of voltage of sensor 1 with convolution kernel function (5). From Fig. 6 we can find that the estimation value is very

stable with the increasing number of neighbors. If we choose 9 or 10 neighbors the estimation value is 2.664751. It is very close to the real value because the voltage values from different sensor at the same epoch are very similar.

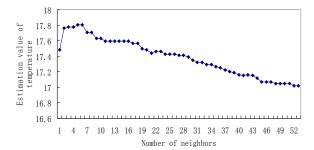


Fig. 5. The estimation value of temperature with convolution kernel function (6).

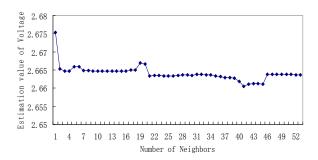


Fig. 6. The estimation value of voltage with convolution kernel function (5).

4. Conclusion

In this paper, we propose a new missing value estimation algorithm based on convolution theory in wireless sensor network. Through what we have discussed above, we can find that choose an appropriate convolution kernel function and an appropriate group of neighbor sensors are both critically important for data estimation. For different environment variables, the kernel function should be different because each of them has its own characteristics and the number of neighbors can not be too small or too large. In the further, we will continue to research to find the appropriate kernel functions to improve the accuracy of this algorithm by analyzing each environmental variables and the temporal factor will be taken into consideration.

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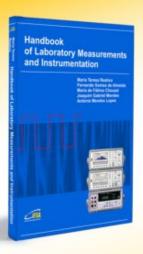
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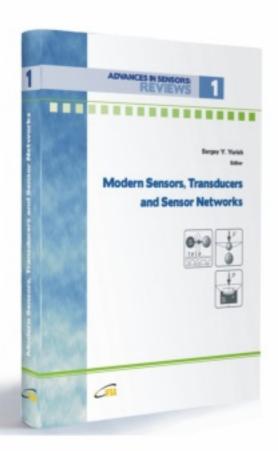


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