Dynamic Control of Data Measurement Intervals in a Networked Sensing System using Neurocomputing

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***Abstract*—A new algorithm for dynamic controlling of data measurement intervals in a networked sensing system (NSS) is presented in this paper. The method is developed on a wireless sensor network (WSN) for food quality supervision during the transportation process using containers. The artificial neural network (ANN) is used for data approximation due to its learning capability and high flexibility. At each instance, the measurement interval is changed dynamically depending on the stability of the environmental parameters in the container. The wireless sensor network is able to detect the possible unstable situations automatically with low energy consumption. Firstly, the performance of the dynamic control mechanism is tested in a simulation environment. Later, the developed algorithm is implemented to adjust the measurement intervals in a real transportation system. The new developed technique could be applied to decrease the power consumption in various applications of the networked sensing systems.**

***Index Terms*—artificial neural network, dynamic measurement interval, intelligent transportation, networked sensing system**

I. Introduction

To transport any perishable and sensitive freight, it is necessary to monitor the environment in the transportation system online. Wireless sensor networks are appropriate tools to perform this logistical task due to their low energy consumption, high flexibility and robustness. The intelligent container, which is developed by CRC637 project in University of Bremen, combines the RFID technologies and wireless sensor networks for autonomous transportation purposes [1]. The WSN is used to monitor the environment and make decentralized decisions according to the requirements of the transported freight. Normally, the WSN senses the environmental parameters, e.g. temperature and humidity, with a fixed sampling frequency. Although adjusting a high sampling rate is relatively safe but it could cause a lot of redundant data and high energy consumption to establish a stable transportation process. Basically, sensor nodes have extremely limited power resources (batteries). If the sensor nodes are able to adjust the stability of the environmental parameters and adapt the data measurement interval accordingly, the energy consumption can be reduced. In order to determine the interval for the next measurement, a predictor is needed to approximate the development trend of the sensor readings. The artificial neural network is chosen for this work due to its learning capability from the previous and current data values as well as the sensitivity to track the parameter changes. For continuous data training and approximation the training set and network architecture could be dynamically updated. In this work the developed algorithm is evaluated in both simulation environment and real application, i.e. a single-hop WSN in the container for the food transportation.

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II. Related Works

Many works about the variable sampling interval were carried out. Irvine et al. altered the data sampling rate for low-power Microsystems depending on the data approximation accuracy [2]. The Modified Adams Method was used as data predictor. If the prediction error exceeds the given tolerance (tol), the sampling step will be halved; also, when the prediction error is smaller than tol/2, the sampling rate will be doubled. Another method called variable sampling interval $\overline{X}$ chart (VSI $\overline{X}$ Chart) [3] was introduced by Reynolds et al. A target value and a signal region are given to be compared with the sample mean values $\overline{X}$. A long sample interval will be taken, when $\overline{X}$ is closer to the target value. If $\overline{X}$ is close to the signal region, a more intensive sampling rate is used. Mark et al. introduced a Level-Crossing sampling approach [4]. This sampling method uses a number of threshold levels, which have the same amplitude step size. If the input signal crosses a level, a new sample will be taken. Many studies about adaptive sample rate were based on the Level-Crossing approach [5, 6].

III. Dynamic Measurement Interval Algorithm

Fruit and vegetable transportation requires usually a relatively stable environmental condition. An upper and lower temperature boundary can be determined for different types of freight according to the quality loss model [7]. The algorithm of dynamic data measurement interval calculates the next sensing interval according to the difference between the current temperature reading and temperature boundaries and the predicted temperature variation (Fig. 1). Since the measurement interval control of the Humidity is the same as that of the temperature, this algorithm is valid for both environmental parameters; thus, this paper focuses on the temperature measurement interval. The two important parts of the algorithm will be introduced in the following two sections.

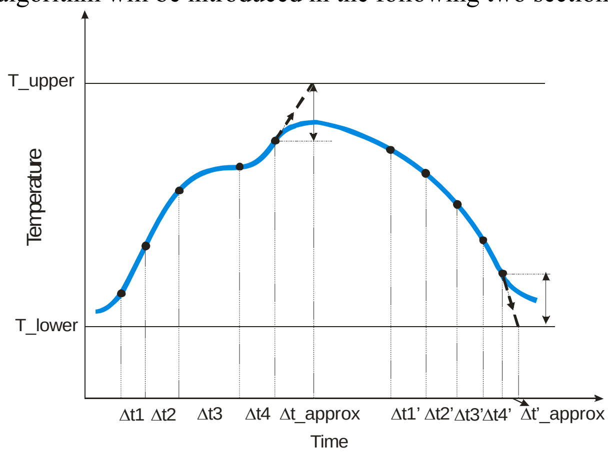

Fig. 1: Concept of the dynamic control of measurement intervals

A. Data approximation with neural network

ANN is capable of modeling complex functions which makes them favorite to solve the regression problems. The main advantages of using ANN compared to the other traditional statistical methods are nonlinearity and flexibility. Multilayer perceptron network (MLP) is usually taken into account for global approximation. In this paper, to predict data in the utilized sensor network, the optimized architecture and parameters are selected including two hidden layers (including $\Phi^{(1)}$ and $\Phi^{(2)}$) with four neurons (Fig. 2) [8]. Each time, four sequential temperature increases of each sensor node generate the input pattern. The obtained output $\tilde{x}_n$ is the predicted temperature increase for the next time interval. The network calculates the prediction error and updates itself using the backpropagation algorithm. This procedure continuously updates the input and target vectors to train and predict the temperature increase values $\tilde{x}_n$. In the propagation process the output of the network ($\tilde{x}_n$) is obtained by calculating the output of each neuron of the second hidden layer (1):

$$\tilde{x}_n = \sum_{i=1}^{4} w_i^{(3)} \Phi_i^{(2)} \tag{1}$$

To train the network, a "gradient descent" algorithm is applied to minimize the prediction error. The error (cost function) is defined as the sum of the squares of the output errors of the output neuron in (2).

$$E = \frac{1}{2}\sum [D(k) - \tilde{x}_n(k)]^2 = \frac{1}{2}\sum e^2(k) \tag{2}$$

Whereas D denotes the desired output which is x_n in this application, $\tilde{x}_n$ refers to the actual output. The error function is minimized by updating the weights in the direction of decreasing the error function. Equation (3) shows that the error function is proportional to the negative gradients of the error function and weights (where η is the learning rate):

$$\Delta W^{(3)} = -\eta \nabla W^{(3)} E \tag{3}$$

The weights between the second hidden layer and the output layer are updated ($W^{(3)} = W^{(3)} + \Delta W^{(3)}$). Similarly, the other weights are updated consequently [8].

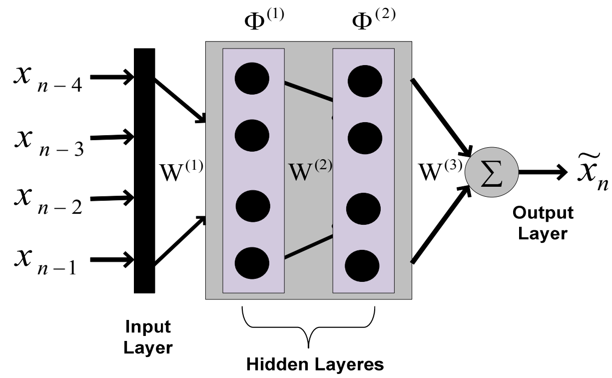

Fig. 2: Two layer sliding backpropagation architecture for data prediction

B. Dynamic control of measurement interval

Since the algorithm calculates the prediction value $\tilde{x}_{n+1}$ of the temperature increase for every single step n, the time interval Δt_{n+1} can be updated continuously depending on the current environmental status in the container with (4).

$$\Delta t_{n+1}[min] = \begin{cases} (T_{upper} - T_n)/\tilde{x}_{n+1} & if\ \tilde{x}_{n+1} > 0 \\ \Delta t_{max} & if\ \tilde{x}_{n+1} = 0 \\ (T_n - T_{lower})/|\tilde{x}_{n+1}| & if\ \tilde{x}_{n+1} < 0 \end{cases} \tag{4}$$

The positive prediction value of the temperature increase shows that the next temperature reading will increase towards the upper temperature boundary, thus the measurement interval is calculated using the difference between the current temperature and the upper boundary. In contrast, a negative prediction value means the temperature decrease and in that case the lower temperature boundary is used. If the temperature keeps constant, the maximum time interval Δt_{max} will be used, which is set to 20 min in this application. Equation (4) describes the algorithm to determine the measurement interval when the temperature varies within the desired range [T_{lower}, T_{upper}]. If the sensor readings exceed the required temperature range, the sensors will measure the parameter with the minimum interval Δt_{min}, which is set to 2 min in this paper. The time interval determined by (4) is the approximated time from the current temperature to one of the two mentioned boundaries. However, if the actual temperature increase is larger than the predicted value or the temperature increase rises in the period, it can cause the risk that the temperature exceeds the boundary within the calculated time interval. Therefore, a coefficient s ($s \geq 2$) should be used to scale the interval in order to ensure a reliable temperature monitoring; however a huge s can cause high energy consumption. In this paper, s = 10 is used, i.e. when 10% of the temperature difference is arrived, the next sample will be taken into account. Therefore, (4) is modified as follows:

$$\Delta t_{n+1}[min] = \begin{cases} (T_{upper} - T_n)/(s \cdot \tilde{x}_{n+1}) & if\ \tilde{x}_{n+1} > 0 \\ \Delta t_{max} & if\ \tilde{x}_{n+1} = 0 \\ (T_n - T_{lower})/(s \cdot |\tilde{x}_{n+1}|) & if\ \tilde{x}_{n+1} < 0 \end{cases} \tag{5}$$

IV. Simulation Results

In this section the accuracy and the convergence time of the predictor to track the temperature changes using the ANN are tested. The performance of the applied approach to change the measurement interval is simulated.

A. Input signal of the simulation

Assuming that the optimal temperature in the container is 0°C and the desired temperature range for the transportation is [-15.0, 15.0] °C. The test data of the algorithm consists of the optimal temperature and the following functions as temperature fluctuations (Fig. 3.):

$$\begin{cases} y_1 = 20 \cdot (sin(0.5t) + sin(t) + sin(2t))/3 \\ y_2 = -20 \cdot (sin(t) + sin(2t))/2 \end{cases} \tag{6}$$

B. Prediction of temperature change

To test the accuracy of ANN mechanism to predict the temperature variation, the time interval is kept constant (1 min). The ANN exhibits four input sets, i.e. the temperature increase approximation $\tilde{x}_n$ for time point n is calculated corresponding to the last four temperature increase records: $\tilde{x}_n = f(x_{n-1}, x_{n-2}, x_{n-3}, x_{n-4})$. The inputs of ANN have higher priority to decide the prediction output, but the memory about the previous environmental information kept in the weights between the hidden layers can provide useful references to make a better decision. The priority of the inputs is decided by the learning rate η. In Fig. 4(a) the predicted and the actual temperature variation curves are compared with each other and Fig. 4(b) shows the approximation errors E_{approx}. E_{max} denotes the maximum prediction error in the differentiable area, i.e. $\exists dE_{approx}/dt$. The ANN shows a sufficient data prediction, whereby the maximal prediction error $|E_{max}| = 0.055$°C/min.

Since the initial weights of the MLP are determined randomly, the prediction error E_{approx} can be extremely high in the first few prediction cycles. The time to reach the $|E_{approx}| \leq 0.01$ °C/min is considered as the initial phase. The length of initial phase depends on the learning rate η. $\eta \geq 0.9$ slows the convergent process down due to the oscillations and $\eta \geq 1.2$ leads to a high risk that the approximation does not converge at all. The maximal prediction error E_{max} and the length of the initial phase with different η values are compared to each other to choose the suitable η (Fig. 5). The results show that E_{max} decreases if η increases, while the convergence time of the initial phase reaches the minimum value (7 min) when $\eta = 0.8$. Therefore, $\eta = 0.8$ is chosen as the optimal learning rate for this research.

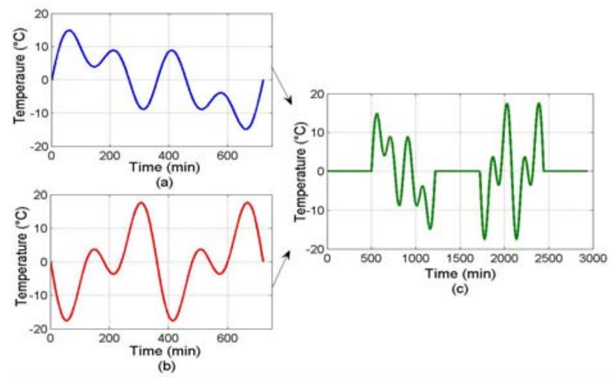

Fig. 3. The input signal for the simulation of the dynamic time interval algorithm. (a) Fluctuation signal y_1 = 20 (sin(0.5t)+sin(t)+ sin(2t))/3 (b) Fluctuation signal y_2=-20 (sin(t)+ sin(2t))/2. (c) the simulation input data

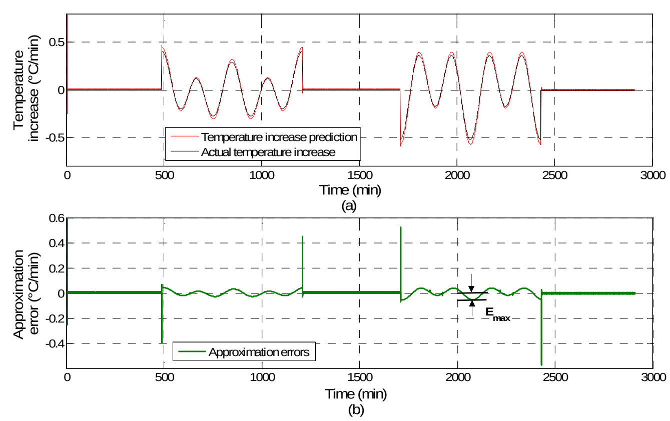

Fig. 4. Simulation results of predictor with neural networks. (a) Actual and predicted temperature increase of the simulation (b) Prediction error E_{approx}.

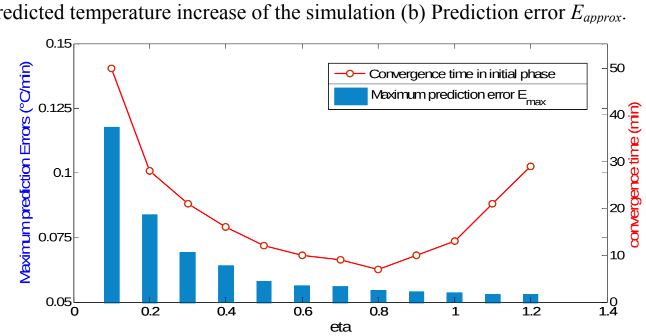

Fig. 5. Maximum error E_{max} and the convergence time of the initial phase with different learning rate η

C. Dynamic measurement intervals

In this section the dynamic control algorithm of the measurement intervals is tested. The temperature input signal and the correspondent measurement intervals are shown in Fig. 6(a). The trend of temperature development and the temperature boundaries are adjusted autonomously. The algorithm can accelerate the temperature measurement accordingly, once an unexpected temperature oscillation is detected, even though the sensor readings are still within the desired range. The temperature increase records with deduced measurements are given in Fig. 6(b). Compared with the original records (Fig. 4(a)), the most important information about the temperature changes are detected, although nearly 87% of the measurements are reduced.

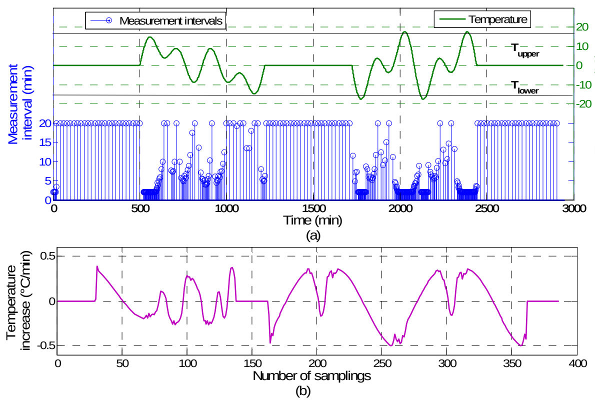

Fig. 6. (a) Dynamic intervals according to the temperature changes. (b) Recorded temperature increase with dynamic intervals.

V. Implementation results

The developed algorithm is implemented in a WSN which consists of TelosB sensor nodes containing a temperature and humidity sensor SHT 11. The practical experiments are performed in a TEU (Twenty-foot equivalent unit) container.

A. Test environment

Seven TelosB sensor nodes are located in different positions inside the empty container. Arbitrary set points between are used to set the reefer unit temperature inside the driver cabin to establish the practical transportation conditions. Six sensor nodes are divided in three pairs to record the temperature inside the container; each pair consists of a node with a constant interval and a node with dynamic control features. Another sensor node attached on the wall acts as the data sink to collect the temperature data from all sensor nodes and forward them to an indicator in the driver cabin. The ambient temperature is 18°C. In order to test the plausibility of this algorithm, an extreme condition is used in this work, i.e. the temperature range of [-10.0, +10.0] °C, which is much larger than the temperature deviation in a real transportation.

B. Test results

The temperature records from one pair of sensor nodes for 822 min are shown in Fig. 7 as an example. The temperature curves are divided in two main phases. *Phase 1:* where the temperature exceeds the upper boundary +10 °C and is measured intensively with the minimum time interval Δt_{min}; *Phase 2:* the temperature enters the recommended temperature range and is measured dynamically.

The test results from three sensor nodes pairs show that the temperature measurement with dynamic algorithm reduces more than 84% samplings although the most important information about the temperature changes is recorded. Especially in phase 2 the dynamic algorithm shows greater advantage than the static measurement. When the temperature stays in the desired conditions, only less than 8% of the samplings are taken into account. Every sensor node in the WSN can make decentralized decision about its own sampling rate according to the surrounding environmental condition.

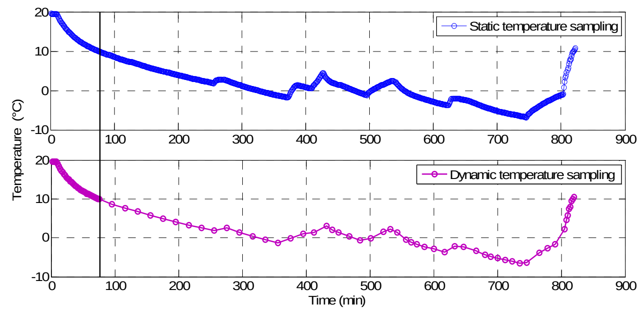

Fig. 7. Temperature records inside the truck with static and dynamic controlling of the measurement intervals

VI. Conclusion

In this paper a novel algorithm was introduced to control the sampling intervals autonomously in a WSN. The applied algorithm consists of two main steps including data variation prediction and dynamic control of measurement intervals. A new application of sliding backpropagation algorithm was presented to predict data increase in WSN. The dynamic control mechanism could adapt the sampling rate according to the current environmental state and the desired temperature range. A temperature variation prediction accuracy of 0.05°C/min and a short convergence time of 7 prediction cycles can be reached using the ANN. Compared to the static mechanism the dynamic mechanism can reduce the samples up to 94% in the practical implementation.

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