Adaptive Data Sensing Rate in Ad-hoc Sensor Networks for Autonomous Transport Application

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Abstract - A novel algorithm for adaptive control of the data sensing rate in wireless ad-hoc sensor networks (WSN) is presented. The WSN is applied to monitor the environmental parameters e.g. temperature and humidity, inside containers for the food transportation. Using the proposed algorithm, each sensor node can control its sensing intervals according to the surrounding environmental conditions. The data sink receives only the required information from data sources, so that the process of data fusion could be optimized by minimizing the overall data transmissions in WSN. In order to approximate the development trend of the environment, a neural network algorithm is used due to its learning capability and flexibility. The algorithm of adaptive sensing rate is tested in a simulation environment and implemented in a refrigerator truck for a food transport purpose. Both the simulation and implementation results show that the algorithm can autonomously concentrate on the problematic situation and efficiently reduce the redundant data measurements.

Keywords: Wireless sensor networks; intelligent transportation system; adaptive data sensing interval; artificial neural network; power consumption

1 Introduction

In modern transport logistics, especially for perishable freights such as vegetables and fruits, the online environment supervision inside the container becomes very important. A large and/or durable deviation from the recommended environmental conditions can cause unexpected quality losses of the freights [1]. Due to the low energy consumption, high flexibility and robustness the wireless ad-hoc sensor networks provide a promising solution for monitoring the environmental parameters e.g. temperature and humidity in the container during the transport processes. To achieve an autonomous transport system, an “Intelligent Container” is developed in the University of Bremen. The “Intelligent Container” establishes a decentralized decision-making system by collecting the freight information from the attached RFID-tags on the goods and the instantaneous environmental information from a WSN, which consists of a number of spatially distributed sensor nodes [2].

Data fusion in a WSN deals with the current and previously obtained records of the participant nodes in order to perform a collaborative decision making. The sampling rate of each participant node has remarkable influence on data fusion efficiency. In this paper, the adaptive data sampling algorithm is developed to minimize the sensory records which could be utilized to optimize data fusion considering the power constraints in the WSN. Usually, all sensor nodes in a WSN sense the physical environment with a fixed and empirically predetermined time interval and afterwards transmit the sensor reading to a data sink. It can lead to missing the important information about the parameter variations in an instable environment. However, if the transport process is stable, a lot of redundant sensing data will be generated, that leads to many useless data communication and fusion processes. It would be more energy efficient, if each sensor node is able to adapt its sensing interval dynamically considering the development trend of the sensor readings and the recommended environmental condition boundaries. For this purpose a precise predictor is needed to evaluate the development trend of the environment. The artificial neural network (ANN) is chosen for this work due to its learning capability from the limited existing information, nonlinear data mapping property and the sensitivity to track the data changes. Different approximation approaches are compared with each other in this paper; the comparison study shows that the neural network method performs high approximation accuracy. In order to test the power efficiency and the sensing quality of the adaptive sensing rate algorithm, it is implemented in a simulation environment as well as in a real transport process with container for about 35 hours.

During the transportation, data sensing with both fixed and dynamical measurement intervals is implemented. Afterwards, the sensory records with different sensing methods are compared to each other.

2 Related works

A lot of studies about the adaptive sensing interval control were carried out. In [3] Irvine et al. controlled the data sampling intervals for the low-power microsystems according to the data approximation accuracy. The authors developed a novel data prediction approach named modified Adams methods (MAM) by combining the forth order Adams-Bashforth and Adams-Moulton methods together. If the prediction error exceeds the given tolerance (*tol)*, the sampling step will be halved; also, when the prediction error is within *tol/2*, the sampling rate will be doubled; otherwise, the current sampling step size will be kept. Mark et al. presented a Level-Crossing sampling approach in [4]. This sampling method uses a number of fixed quantization levels. If the input signal crosses any level, a new sample of the input signal will be taken. Many other studies about adaptive data processing were based on the Level-Crossing approach [5, 6, 7]. Another method called variable sampling interval $\overline{X}$ chart (VSI $\overline{X}$ Chart) [8] was introduced by Reynolds et al. In this method a target value and a signal region are defined to control a certain process. During the process, when the mean value of the samples is close to the target, i.e. the procedure is completely under control, a long sample interval will be used. If the sample mean is near to the signal region, an indication signal of a possible shift of the sample mean from the desired value will be generated. In that case, a more intensive sampling rate will be taken. Another variant of the VSI $\overline{X}$ Chart is VSI CUSUM Chart (variable sampling interval cumulative sum) [9]. In this method the mean $\overline{X}$ is replaced by the CUMUS statistic.

Artificial neural networks deal with the approximation and regression tasks in many applications [10, 11]. Radial basis function (RBF) and multilayer perceptron (MLP) are two main architectures to perform local and global data approximation respectively [12]; Specht introduced "Probabilistic Neural Network" (PNN) and "General Regression Neural Network" (GRNN) [12]. Hybridizing the neural network with other techniques like statistical approaches and fuzzy is used to obtain more accurate regression [13, 14]. Another well-known data approximation technique is the Least Squares (LS). The LS could include linear/nonlinear, partial and weighted architecture to solve the generalized regression and filtering problems [15, 16, 17]. It can be involved in WSN for data fusion; distributed LS localization was studied by Behnke et al. for a WSN [18]. Predd developed a new algorithm for collaborative data processing using a kernel-linear least-squares regression [19]. The LS approximation algorithm was implemented for fault diagnosis in a WSN [20].

3 Algorithm of adaptive data sensing

During the transportation of fruits and vegetables the environmental parameters should always be kept in a desired range. The upper and lower parameter boundary can be either provided by the transport freight information or calculated using a quality loss model for different types of goods [21]. The general idea of the algorithm is to find out the time point for the next necessary sensing. For this purpose, the current value of the parameters, the sensor reading development trend and the recommended environmental condition boundaries must be considered. The algorithm observes a certain number of the sensor readings and approximates the variation speed of the temperature and the relative humidity. The next sensing interval can be calculated with the predicted parameter variation and the difference between the current sensor readings and one of the above mentioned two boundaries (Fig. 1). The algorithm will be explained in detail in the following two sections.

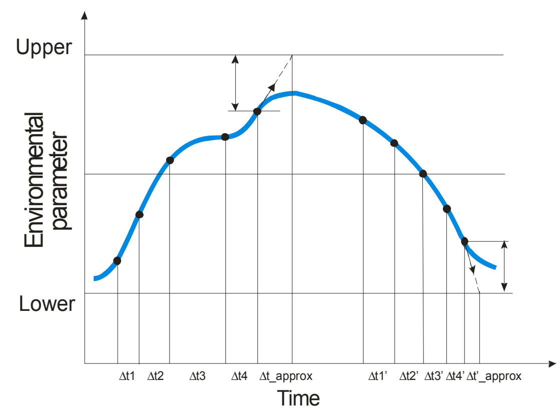

Fig. 1 Principle of the adaptive sensing interval algorithm

3.1 Data prediction with artificial neural networks

Neural network leads to a nonlinear mapping between the input and output using algebraic functions. It requires a certain number of input sets to train the network; the number of input sets, the accuracy of the training, and the parameters of the network greatly influence the accuracy of the approximation. In the typical backpropagation technique, the network is trained according to a defined network architecture, number and dimension of input patterns and target vector [22, 23, 24]. After the training phase, the network is used to approximate data. The application of the traditional backpropagation technique to embedded systems could not be feasible due to the constraints of memory size, processing capability and required energy for the calculation. To overcome these limitations, a sliding backpropagation approach was introduced where the entire network is continuously updated for training and data approximation solely by using a limited number of neurons and samples [25]. Fig. 2 illustrates the proposed criteria to predict the instantaneous value of temperature/ humidity variation speed ($\tilde{x}_n$) using the last sequential obtained records ($x_{n-1}, x_{n-2}, x_{n-3}, x_{n-4}$). The proposed neural network architecture is comprised of two hidden layers; the hidden units include sigmoid activation functions ($\Phi^{(1)}, \Phi^{(2)}$) in two layers which are applied on weighted elements for regression. Various architectures were examined to design the neural network architecture [25]; considering the obtained results the network architecture was chosen according to the Fig. 2.

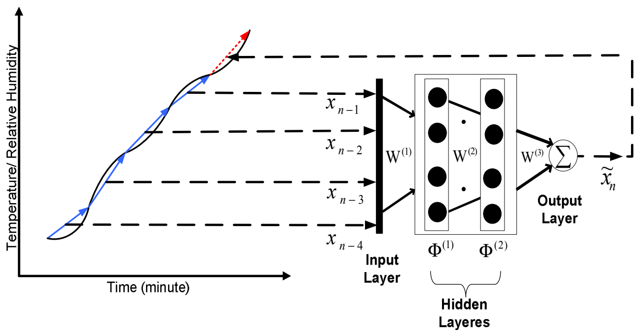

Fig. 2 Applied neural network architecture to predict the variation of the environmental parameters

To train the network at each instance, the error (cost function) is defined as the sum of the squares of the output errors at the output neuron (1) whereas D denotes the desired output and $\tilde{x}_n$ refers to the actual output at each instance (k)

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

The error function is minimized by updating the weight values in the direction of decreasing the error which is proportional to the negative gradients of the error function and weights (2) (where η is the learning rate); $W^{(i)}$ denotes the ith weight vector between the layers.

$$\Delta W^{(i)} = -\eta \nabla W^{(i)} E \qquad i = 1,2,3 \tag{2}$$

3.2 Adaptive control of the sensing intervals

In order to achieve a real-time control of the data sensing rate according to the instantaneous environmental information, the sensing interval should be updated for every single step. The next sensor readings $\vec{P}_n = (T_n, H_n)$ will be taken after the calculated time interval Δt_n. Using neural network with the sliding backpropagation algorithm the parameter variation speed $\vec{\tilde{x}}_n = (\tilde{x}_{nT}, \tilde{x}_{nH})$ is able to be approximated continuously. Since the time interval for temperature (Δt_{nT}) and relative humidity (Δt_{nH}) sensing are calculated in the same way, Δt_{nT} is taken as an example to explain the calculation of the sensing interval. The time interval Δt_{nT} for temperature sensing can be calculated with (3):

$$\Delta t_{nT}[min] = \begin{cases} (T_{upper} - T_{n-1}) / \Delta\tilde{x}_{nT} & if \quad \Delta\tilde{x}_{nT} > 0 \\ \Delta t_{max} & if \quad \Delta\tilde{x}_{nT} = 0 \\ (T_{n-1} - T_{lower}) / |\Delta\tilde{x}_{nT}| & if \quad \Delta\tilde{x}_{nT} < 0 \end{cases} \tag{3}$$

The sign of the predicted value $\Delta\tilde{x}_{nT}$ shows how the temperature will vary. If $\Delta\tilde{x}_{nT}$ is positive, the temperature is increasing towards the upper temperature boundary. Therefore, the next time interval is determined with the increase speed $\Delta\tilde{x}_{nT}$ and the difference between the current temperature and the upper boundary. On the contrary, the negative value of $\Delta\tilde{x}_{nT}$ denotes that the temperature decreases. In this case the lower temperature boundary should be used. In a quite stable environment without temperature changes, the maximum time interval $\Delta t_{\max}$ will be used. In this paper $\Delta t_{\max}$ is set to 30 minutes for the simulation as well as for the practical test in the transportation. Equation (3) is applicable, if the environmental parameters are within the recommended range. However, if either the temperature or relative humidity readings exceed one of the parameter boundaries, the sensors have to sense the environment frequently with the minimum interval $\Delta t_{\min}$, which is set to 2 minutes in this work. The time, which is calculated by (3), is the duration to reach one of the temperature boundaries with the predicted variation speed $\Delta\tilde{x}_{nT}$. To ensure a reliable environment sensing, a scaling factor $s \geq 2$ is taken into account. In this work $s = 10$ is used, i.e. when 10% of the difference between current temperature and a temperature boundary is reached, the next sensor reading will be taken. Therefore, (3) is modified as follows:

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

The relative humidity sensing interval Δt_{nH} can be obtained with the same calculations just with the humidity boundaries H_{upper} and H_{lower}. After the calculation two interval values are obtained: Δt_{nT} and Δt_{nH} for the temperature and relative humidity, respectively. The final time interval is defined by $\Delta t_n = min(\Delta t_{nT}, \Delta t_{nH})$.

4 Simulation results

The algorithm is tested at first in a simulation environment. The temperature and relative humidity sensor readings from a previous practical measurement are used as the simulation input data. The measurement was carried out in an empty container. The environmental parameters were measured using several sensor nodes for 9 hours with a step size of 1 minute. During the practical measurement several faults were generated, e.g. the door of the container was opened shortly and the reefer temperature was altered in a large range [-10.0°C, +10.0°C]; the ambient temperature was about 20°C. The temperature and the relative humidity readings are shown in Fig. 3.

4.1 Comparison of different data predictors

In this section the prediction accuracy of the neural network approach will be tested. For this purpose, two other prediction methods are chosen to compare with neural network. One is the *least squares approximation* (LS) and the other is the *modified Adams method* (MAM), which is used for a variable-rate data sampling rate approach [3].

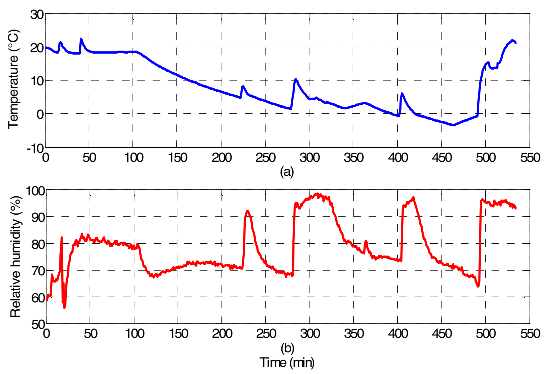

Fig. 3 Input data of the simulation test (a) Temperature (b) Relative humidity

4.1.1 Least squares

The LS technique is developed in signal processing for stochastic approximation and regression. It is established on over-determined equations to model a system. Assuming that the development trend of the environmental parameters can be fitted with a straight line $y = a + bx$. In order to determine the coefficient vector $\vec{c} = (a\ b)$, m ($m > 2$) sensor readings are taken into account as vector $\vec{Y} \in \Re^m$. Matrix $X \in \Re^{m \times 2}$ consists of the index number of the sensor readings. An overdetermined system is obtained: $X\vec{c} = \vec{Y}$. The objective of the LS is to minimize the 2-norm of the error vector $\vec{e}$ [26]:

$$\|\vec{e}\|^2 = \left\|X\vec{c} - \vec{Y}\right\|^2 = \left(X\vec{c} - \vec{Y}\right)^T \left(X\vec{c} - \vec{Y}\right) \tag{5}$$

For this purpose the gradient is set equal to zero, and the following equation can be obtained to calculate the coefficient vector $\vec{c}$:

$$\vec{c} = \left(X^T X\right)^{-1} X^T \vec{Y} \tag{6}$$

4.1.2 Modified Adams method

A so called modified Adams method is introduced for data prediction in [3]. The forth-order Adams-Bashforth and Adams-Moulton methods are combined as the data predictor and corrector. The idea of the approach is to approximate the next data value (y_{n+1}^p) by adding the potential increase ($hf(t,y)$) to the current value (y_n) (7). Here, ($f(t,y)$) is the slope and h is the length of the next time interval.

$$y_{n+1}^p = y_n + hf(t,y) \tag{7}$$

The forth-order modified Adams methods simplify the Newton-Gregory polynomial integration (8):

$$y_{n+1} = y_n + \int_0^1 \left(f_n + \frac{s}{1!} f_n' + \frac{s^2 + s}{2!} f_n'' + \frac{s^3 + 3s^2 + 2s}{3!} f_n''' \right) hds \tag{8}$$

to (9):

$$y_{n+1}^p = \frac{\left(509 y_n - 534 y_{n-1} + 336 y_{n-2} - 146 y_{n-3} + 27 y_{n-4}\right)}{192} \tag{9}$$

Equation (9) can be used to predict the next sensor reading with five previous data values, only if the six readings are sampled with the same time intervals. In order to compare the prediction accuracy of the different predictors, a fixed sensing interval of 1 minute is used for the three approaches. Therefore, the parameter increase speed Δx_n can be predicted with (10):

$$\begin{aligned} \Delta\tilde{x}_n &= y_{n+1} - y_n \\ &= \left(317 y_n - 534 y_{n-1} + 336 y_{n-2} - 146 y_{n-3} + 27 y_{n-4}\right)/192 \end{aligned} \tag{10}$$

4.1.3 Results of the accuracy comparison

The three approximation approaches are applied to predict the parameter increase speed Δx_n for the input temperature and relative humidity data (Fig. 3). The root mean square errors (RMSE) of the prediction are calculated for N readings (in this work N = 60 min $\times$ 9 hours = 540) in (11).

$$E = \sqrt{\frac{\sum_{i=1}^{N} e_i^2}{N}} = \sqrt{\frac{\sum_{i=1}^{N} \left(\Delta\tilde{x}_i - \Delta x_i\right)^2}{N}} \tag{11}$$

The results of the prediction error for temperature and relative humidity variation speed are shown in Fig 4(a) and 4(b), respectively.

The simulation results show that the neural networks perform the most accurate prediction for the both environmental parameters. Compare to LS the MAM approach operates more accurate prediction for temperature, despite inaccurate approximation for relative humidity. The reason is that MAM uses Newton-Gregory (N-G) backward differencing approximations to calculate the derivatives, e.g.:

$$f_n' \approx \frac{f_n - f_{n-1}}{h}\ , \qquad f_n'' \approx \frac{f_n - 2f_{n-1} + f_{n-2}}{h^2}$$

This approximation will bring huge prediction errors at the positions, where the drastic nondifferentiable change of the parameter appears (such as Fig 3(b)).

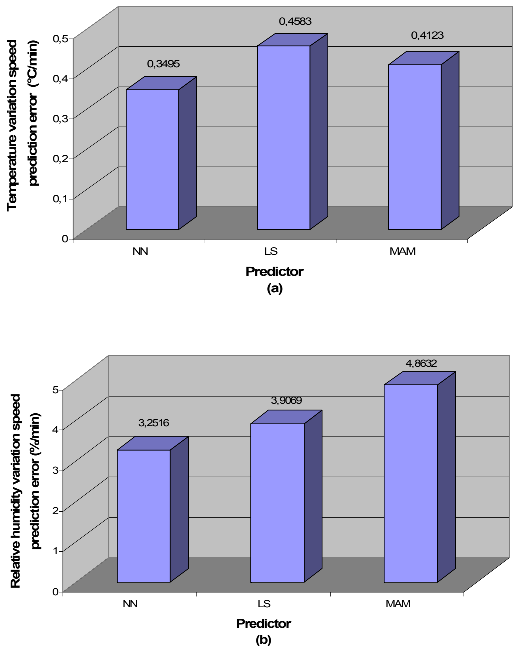

Fig. 4 Accuracy comparison of three predictors for (a) temperature and (b) relative humidity: neural networks (NN), least squares (LS) and modified Adams methods (MAM)

4.2 Choice of the neural network architecture

During the transport process the temperature and relative humidity have to be observed and approximated simultaneously. The neural network architecture in Fig. 2 is used to evaluate a single parameter. However, this structure is able to be extended to form more complex architectures for two different parameters. In this work two different architectures are investigated (Fig. 5).

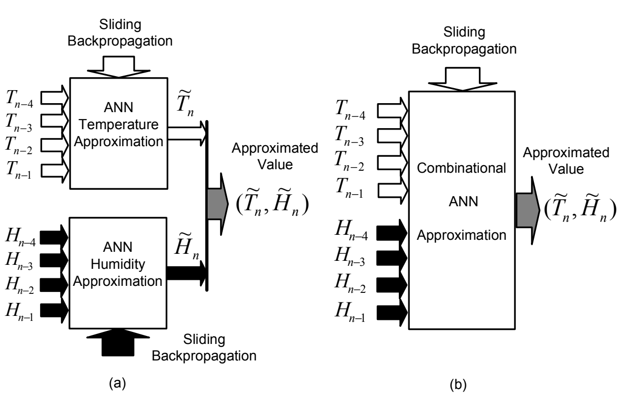

Fig. 5 Different ANN architectures (a) Architecture I: two-stage ANN (b) Architecture II: combinational ANN

Architecture I is the two-stage ANN, i.e. two ANNs are used for temperature and humidity prediction, separately. Architecture II is the combinational ANN, whereby the prediction of the both parameters is achieved with a larger ANN with eight inputs and two outputs. The prediction RMSE (9) is calculated 100 times for each architecture. The mean value ($\overline{E}$) and the standard deviation (σ) of the RMSE for temperature and relative humidity with architecture I and II are given in Table 1.

Table 1. Comparison of two different neural network architectures

	Temperature (°C/min)		Humidity (1/min)	
	$\overline{E}$	σ	$\overline{E}$	σ
Architecture I	0.3398	0.0035	3.3772%	0.2236%
Architecture II	0.3438	0.0080	3.6227%	0.4961%

The results show that architecture I performs more accurately and stably than architecture II. The reason is that, architecture II exhibits the mixed weights and the combined propagation and backpropagation processes for the temperature and relative humidity. The weights matrices have to consider the changes of both parameters, thus, the interaction between the prediction processes of the parameters can alloy the accuracy.

4.3 Dynamic data sensing intervals

The developed algorithm enables the sensor node to evaluate the surrounding environment autonomously and adapt its own sensing intervals accordingly. The sensitivity of the algorithm to track the parameter changes is tested in this section. As mentioned before, several rough faults were generated purposely in the experiment scenario, such as door openings and large reefer temperature variations. Thus, the plausibility of the algorithm can be tested even under the extreme conditions, which are unexpected in a usual transport process. The desired temperature and relative humidity range for the simulation are defined as [-10°C, +15°C] and [55%, 95%]. The test results are illustrated in Fig. 6.

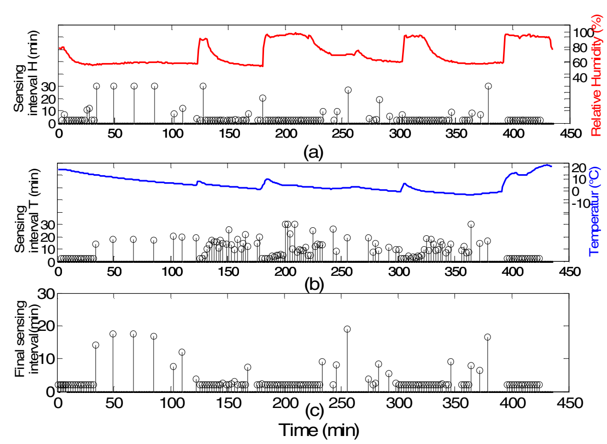

Fig. 6. Simulation results of adaptive data sensing intervals according to (a) relative humidity (b) temperature (c) final sensing interval.

The sensing intervals in Fig 6(a) and (b) are calculated corresponding to the temperature and the relative humidity, respectively. For a certain time point the smaller one of the two calculated intervals is chosen as the final sensing interval for both parameters (Fig. 6(c)). The results show that when the environmental parameters are stable within the recommend range, the sensing is slowed down. If the noticeable variations appear even though still within the desired range, the sensing is accelerated accordingly. Compared to the sensing with fixed intervals, the new algorithm can concentrate the energy consumption more efficiently on the problematic situation.

5 Implementation

The algorithm is implemented in a wireless sensor network (WSN), which consists of the TelosB sensor nodes by the Crossbow Company. This WSN is used for the online monitoring inside a refrigerator truck during a transport process. The size of the cargo hold is equivalent to a standard two-TEU (Twenty-foot equivalent unit) container. The cargo hold was divided in two parts: deep freezer area and fresh area. Each area has its own reefer unit. The scales of the container and the distribution of the sensor nodes of the network are illustrated in Fig.7.

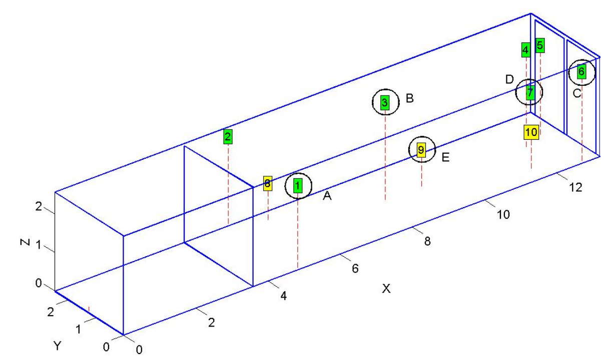

Fig.7. Scales of the container and the distribution of the sensor nodes in the fresh area (A-E are the five zones for algorithm test)

In this test only the environment in the fresh area is considered, in which the recommended temperature and relative humidity range are [0°C, 7.0°C] and [60%, 95%], respectively. Five different zones (A, B, C, D and E) are chosen to test the algorithm of adaptive data sensing intervals. In every zone two different sensing approaches are applied: the adaptive sensing rate algorithm and the fixed interval approach with a step size of 2.5 minutes as reference. The transport duration is 35 hours (= 2100 minutes). The numbers of the sensor measurements with the suggested adaptive intervals from different zones are compared with the reference reading number in Table 2. The results in Table 2 show that the adaptive sensing interval algorithm saved 70% - 75% sensor readings compared to the reference measurement with the fixed intervals. The performance of the algorithm is presented in detail using the records from zone A as example. The interpolated reference temperature and relative humidity measured in zone A and the corresponding sensing intervals are shown in Fig. 8.

Table 2. Sensing Ratio of different zones

	#sensor readings	sensing ratio
Reference (fixed interval of 2.5 min)	2100/2.5 = 840	1:1
Zone A	228	1: 3.68
Zone B	243	1: 3.46
Zone C	262	1: 3.21
Zone D	224	1: 3.75
Zone E	244	1: 3.44

It is indicated that the sensing interval algorithm is sensitive to track the environmental changes. In the instable situations, e.g. the beginning phase of cooling down (0-100 minutes) and the loading phase (210-300 minutes), the minimum interval is used. During the transport the environmental parameters are quite stable and the sensing interval is autonomously switched to the maximum value. From the 25th hour some small fluctuations appear within the desired range. The sensing intervals vary autonomously depending on the potential risk, that the environmental parameters could exceed the recommended range.

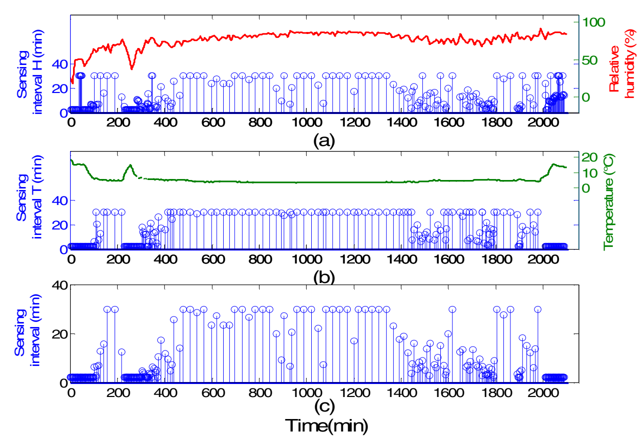

Fig. 8 Applied sensing intervals during the transport process (a) calculated necessary intervals for humidity (b) necessary intervals for temperature (c) final applied sensing intervals for both parameters

In order to test the sensing quality of the algorithm and to prove its capability to enhance the power consumption distribution, a further investigation is carried out in the simulation environment. The certain number of samples (e.g. 228 for zone A, see Table 2) are distributed evenly for the entire transport duration, thus a fixed sensing interval can be obtained (e.g. 2100/228 = 9 minutes for zone A). The sensor readings with the calculated fixed intervals are presented in Fig. 9(c) and Fig. 10(c). In contrast to the adaptive sensing approach, the fixed sensing interval approach is not able to provide enough information about the environmental fluctuation and wastes the most energy to monitor the stable environment. Although the both approaches (Fig. 9 (b) and (c), Fig. 10(b) and (c)) consume the same energy for collecting data, the algorithm of adaptive sensing interval performs a better sensing efficiency. Several extreme values of temperature (a-e) and relative humidity (f - k) curves are marked in Fig. 9 and 10. They are used to prove if the

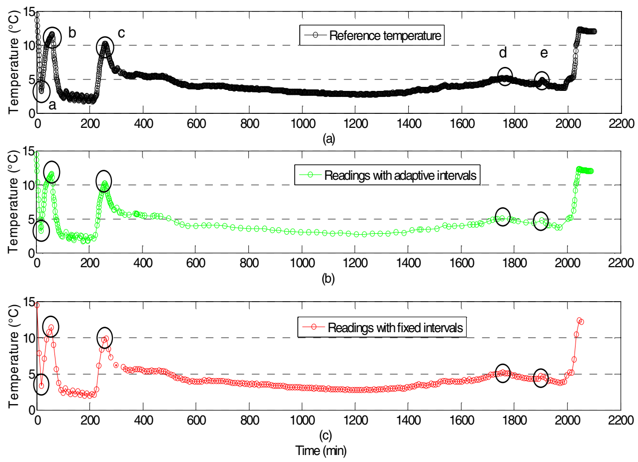

Fig. 9 Temperature sensor readings in zone A: (a) reference records with fixed interval of 2.5 min (b) records with adaptive sensing intervals (c) records with the same number of samples with (b), whereby the samples are evenly distributed in the entire process.

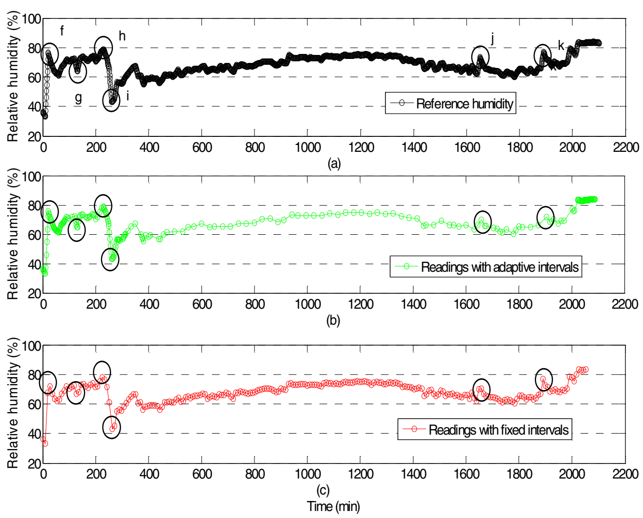

Fig. 10 Relative humidity sensor readings in zone A: (a) reference records with fixed interval of 2.5 min (b) records with adaptive sensing intervals (c) records with the same number of samples with (b), whereby the samples are evenly distributed in the entire process.

dynamic sensing approach can cover all important information about the transport procedure. The results are given in Table 3. The results indicate that the adaptive sensing algorithm records almost all of the most important environmental variations during the transport process due to its sensitivity to the parameter changes. Compared to the approach with fixed intervals the adaptive algorithm doesn't need any empirical predetermination of the sensing intervals and performs a better sensing quality. The disadvantage of the algorithm is that some very short fluctuations (e.g. j and k) probably can be missed in a quite stable environment, since a large interval is used.

Table 3. Comparison of sensing quality with adaptive and fixed Sensing interval

Test point index	Reference value	Record with adaptive interval	Record with fixed interval
Temperature (°C)			
a*	3.32	3.32	3.33
b	11.63	11.63	11.41
c	10.19	10.16	9.84
d	5.10	5.10	5.06
e	4.76	4.76	4.67
Relative humidity (%)			
f	76.34	75.17	71.98
g*	64.59	64.60	68.11
h	78.56	78.56	77.87
i*	43.02	43.02	43.20
j	73.29	69.54	69.85
k	75.80	71.72	72.52

* minimum value

6 Conclusion

A new algorithm of adaptive data sensing interval in wireless sensor networks for transport logistic application is presented in this paper. The algorithm is able to evaluate the environmental parameters inside the container and adapt the sensing intervals accordingly. The environment evaluation is based on the data approximation using a neural network, which performs high prediction accuracy compared to several types of data predictors. The developed adaptive sensing interval algorithm is tested in a simulation environment as well as implemented in a real transport process. The test results show that every sensor node can make local decision about its own sensing intervals and using the algorithm 70% to 75% of the data sensing is saved compared to the fixed interval approach, that can be used in purpose of optimizing the data fusion in resource limited wireless sensor networks. The algorithm enhances the sensitivity of the sensor to track the environment fluctuations and the distribution of the energy consumption during the entire transport process.

Acknowledgement

This research was supported by the German Research Foundation (DFG) as a part of the Collaborative Research Centre 637 "Autonomous Cooperating Logistic Processes".

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