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Multi-sensors data fusion system for wireless sensors networks of factory monitoring via BPN technology

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ABSTRACT

This study attempts to apply a back-propagation network (BPN) for multi-sensors data fusion in a wireless sensor networks (WSNs) system with a node-sink mobile network structure. This investigate is to finish the factory monitoring at environment monitoring services (EMS). These practice wireless sensor network circuits include temperature, humidity, ultraviolet, and illumination four variable measurement components. These data fields of each sensor nodes contain the properties and specifications of that signal process rules, the remote engineers can manage the multi-sensors data fusion using the browser, and the WSNs system then classification the data fusion database via the Internet and mobile network. Moreover, The BPN training approach is significant that improves data fusion system in accuracy and classification with parallel computing for data fusion efficiency. The final phase of the classification fusion system applies parallel BPN technology to process data fusion, and can solve the problem of various signals states. This study is considered implemented on the Yang-Fen Automation Electrical Engineering Company as a case study. The experiment is continued for six months, and engineers are also used to operating the web-based classification fusion system. Therefore, the cooperative plan described above is analyzed and discussed here. Finally, these papers propose the tradition methods compare with the innovative BPN methods.

1. Introduction

Wireless sensor networks have emerged as a new information-gathering paradigm based on the collaborative effort of a large number of sensing nodes. This paper describes the application of BPN technology in the problem domain of sensor data fusion. A sensor network consists of many spatially distributed sensors called nodes, these nodes are used to monitor or detect various kinds of changes in vibration, pressure, movement or pollutant levels. In this investigation, we design four various sensors in the experiment circuit boards include temperature, humidity, illumination, and ultraviolet measurements for EMS. These nodes are usually small and inexpensive in order to allow them to be deployed on a large scale. These are sensors usually have a wireless link which can be used to extract the information captured by the sensor.

A sensor node has a small microcontroller, and an energy source, usually a battery. In order to meet the objective of these sensors being small and low-cost, resources in terms of energy, memory, computational speed and bandwidth are severely constrained. The sensors use each other to transport data to a monitoring entity. Because each sensor has a limited energy supply, sensors must conserve their energy if the network is to last a long time. Wireless, database technology such as queries, and networking technology especially, multi-hop routing protocols to communicate with other nodes is crucial technologies. Wireless technology is used in a type of network, a wireless sensor network. ZigBee is a wireless protocol used by IEEE 802.15.4 association and ZigBee alliance. In this study, the networks need be able to self-organize via ZigBee wireless protocol. The same type of aggregate data with variances needs to be grouped and fused into a single datum for intelligent interpretation. Major limitations included limited storage and power. A special node which connects to a computer and outside the network is called the gateway node.This paper describes the application of BPN technology in the recognition and classification of multi-sensors data fusion. The first section of this paper introduces and reviews the problem presented by sensor fusion. The second section provides the background on BPN and sensor data fusion. The subsequent section discusses the domains where neural-network is applied for sensor data fusion varying as wide as intelligent waste-water management to military surveillance. We provide a model for wide-area surveillance using BPN based multi-sensors data fusion. Finally, we also discuss how precise modifications to BPN can improve the classification level of sensor fusion.

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2. Related literatures

WSNs are composed of a large number of nodes with sensing capability (Akyildiz, 2002). The applicability of such networks includes several areas such as environmental, medical, industrial, and military applications. Usually, WSNs have strong constraints regarding energy resources and computational capacity. In addition, these networks demand self-organizing features to autonomously adapt themselves to eventual changes resulting from external interventions, reaction to a detected event, or requests performed by an external entity (Franceschini, 2007). In general, WSNs are deployed in environments where sensors can be exposed to conditions that might interfere with the sensor readings or even destroy the sensor nodes. As a result, sensor measurements may be more imprecise than expected, and the sensing coverage may be reduced. A natural solution to overcome failures and imprecise measurements is to use redundant nodes that cooperate with each other to monitor the environment. However, multi-sensors data fusion comprises theories, algorithms, and tools used to process several sources of information generating an output that is, in some sense, better than the individual sources (Aquino et al., 2007).

This investigation implements a BPN in multi-sensors data fusion for recognition and classification. The type of recurrent neural network used is known as the multilayer feed-forward network. The BPN provides the basis for nonlinear associative memory. Significantly, the BPN is very effective in data fusion for recognition and classification (Brouwer, 2000a, 2000b). Supervised learning is achieved through the error back-propagation algorithm. In the literature (Hu, Lin, & Wu, 2008), the authors described multi-source data fusion and management for virtual wind Tunnels and physical wind tunnels, the system always adopts the latest data fusion and database conceptions via BPN. In Loskiewicz et al. researches (Loskiewicz-Buczak & Uhrig, 1993), a diagnostic system design which performs evidence aggregation from many sensors in order to automate the interpretation of vibration spectra. The decision system proposed is an active system which its module is a BPN system. The method proposed is very general and can be used for any problem involving aggregation of decisions for the purpose of classification. According to above-mentioned, the data fusion employed BPN is better than traditions methods in recognition and classification based on WSNs (Jayasimha, Iyengar, & Kashyap, 1991; Kumar et al., 2003; Qi, Iyengar, & Chakrabarty, 2001; Sharples, Callaghan, & Clarke, 1999; Varshney, 1997; Varshney & Mohan, 2005; Zhao, Liu, Liu, Guibas, & Reich, 2003).

3. Systematic architecture for EMS

WSNs combining the mobile computing, telecommunication and sensing equipments can operate automatically with least power consumption. The WSNs applications include the monitoring of wild animals, environment monitoring/forecast and health monitoring. This paper intends to use Motes wireless sensor networks, which enable data collection covering soil and air humidity, air temperature, light and ultraviolet. All data from every sensor can be transmitted via ZigBee network transmission protocol, thus forming a mobile WSNs. The EMS data are sent back to the rear database via wireless network and mobile telecom network, thereby contributing to real-time and continuous monitoring of drought. The EMS model decision system automatically analyses the environmental drought data and the results are sent to the end users in real-time. This reduces human error for a more accurate EMS. In Fig. 1, sensor node is capable of detecting and collecting the environmental data. Sensor node processes the collected data and transmits them to the sink node. Sink node is a gateway node, which is responsible for receiving the sensor data and retransmitting these data to the manager node via Internet or mobile networks. Manager node is responsible for processing and displaying the sensor data.

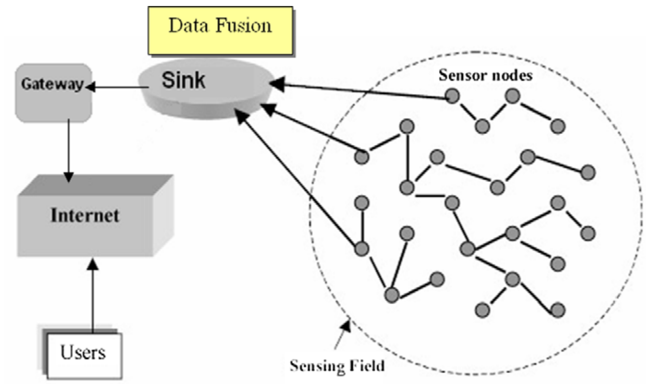

Fig. 1. The system architecture for EMS based on WSNs.

Fig. 2 depicted our WSN nodes device that comprises the sensing units, processing units, transceiver units and power units. The functionality of the units is described as follows:

(1) Sensing unit. A sensing unit comprises the sensor and the analog-to-digital converter. The sensor is responsible for detecting and collecting the environmental data, which represent with the analog signals. The analog-to-digital converter converts the analog signals into the digital data and sends the data to the processing unit. Sensing Unit include temperature, humidity, ultraviolet, and illumination.
(2) Processing unit. Processing unit comprises the processor and the storage unit. Storage unit stores the collected environmental data. Processor processes the data according to the pre-defined program codes.
(3) Transceiver unit. Transceiver unit is responsible for the communications between the sensor devices.
(4) Power unit. Power unit provides the electric power and is the most important unit of a WSN device.

4. BPN algorithm for data fusion in recognition and classification

The acquired data is first subjected to preprocessing step in a sensor node with various sensor components. Besides filtering for noise removal, this step also processes the signal for achieving invariance to selected inspection parameters. For instance, in the case of inspection data fusion at different inspection frequencies the signals are first transformed to an equivalent signal at a reference value of the inspection frequency parameter. Similarly, the overall classification performance of the system can be rendered invariant to other selected parameters (Polikar, Udpa, Udpa, & Taylor, 1998). In the second step, discriminatory features in the signal are extracted. Feature extraction serves to reduce the length of the data vector by eliminating redundancy in the signal and compressing the relevant information into a feature vector of significantly lower dimension. The Discrete Wavelet Transform (DWT) is particularly effective at extracting features at multiple resolution levels in ultrasonic signals which are inherently non-stationary in nature (Polikar, Udpa, Udpa, & Spanner, 1998). A second set of features based on Principal Component Analysis (PCA) also calculates the statistical properties of a set of neighboring A-scans (Bae, Udpa, Udpa, & Taylor, 1997).

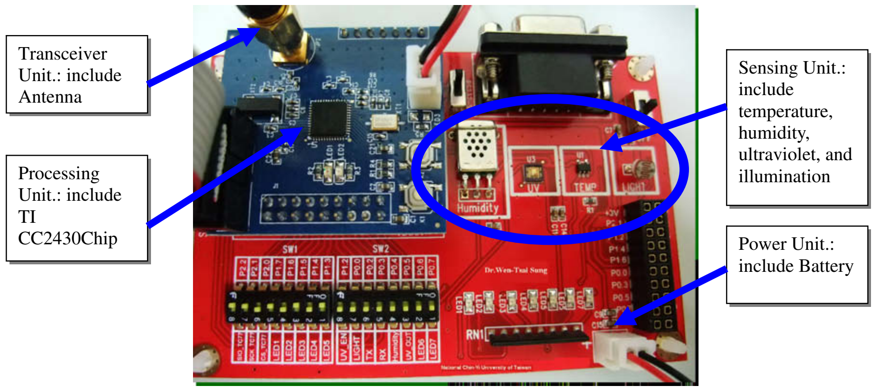

Fig. 2. These devices of sensor node in EMS are built via our researches.

Neural networks are perhaps the most commonly used algorithm in automated classification of signals (Bae et al., 1997). These networks have proved to be extremely effective in learning subtle differences in signals from various classes (indications) as shown in Fig. 3. A neural network classifier with the error back-propagation training algorithm is used in the signal classification system developed in this study. The objectives of the paper were focused on demonstrating the four different signals classification system on TI CC2430 Chip. The demonstrations were conducted using BPN procedure qualification test but on a smaller scale. The final phase of this work will focus on the development of a commercial quality windows-based software package for automated EMS data fusion. This paper utilizes the most prevailing BPN algorithm to analyze the potential degrees for EMS measurements. The BPN algorithm is a typical supervised learning network (Ye, 2004), which is to learn the internal reflection and regulations between inputs and outputs. The regulations are the synaptic weights of network neurons. For analyzing any new cases, the input values or independent variables are inputted into the neural network and get the inferential related output values quickly. BPN have three system layers and described as follows:

(1) Input Layer comprises the inputs of the BPN and represents the initial values of decision.
(2) Hidden Layer comprises the neurons, which are responsible for adjusting the synaptic weights of neuron linkages and determining the suitable synaptic weights. To have accuracy results, the hidden layer is composed of several sub-layers to learn the internal reflection and regulations between inputs and outputs.
(3) Output Layer comprises the outputs of the BPN and represents the final decision results at this training operation.

The control procedure of the EMS based on BPN algorithm divides into the following operation steps:

(1) Set up the network parameters.
(2) Set up weighted matrixes, i.e., *W_xh* and *W_hy*, and the initial values of bias vector, i.e., θ_h and θ_y, by uniformly random numbers.
(3) Calculate the output quantity of the hidden layer.
(4) Set up the tolerant difference quantity between the output layer and the hidden layer.
(5) Calculate the difference quantity, i.e., δ, between the output layer and the hidden layer.
(6) Determine whether the difference quantity between the output layer and the hidden layer is greater than the tolerant difference quantity Φ. If the difference quantity δ is smaller than the tolerant difference quantity Φ, the optimal regression model is obtained.
(7) If the difference quantity δ is greater than the tolerant difference quantity Φ, the weighted matrixes *W_xh* and *W_hy*, and the corrections of bias values θ_h and θ_y in the output layer and the hidden layer have to be computed.
(8) Revise the weighted matrixes and the bias values in the output layer and the hidden layer, and repeat steps (3)–(7) until the difference quantity lies within the range of the tolerant difference quantity.
(9) Finally, compare the correlation of sensitivity correction to find out the optimal regression model.

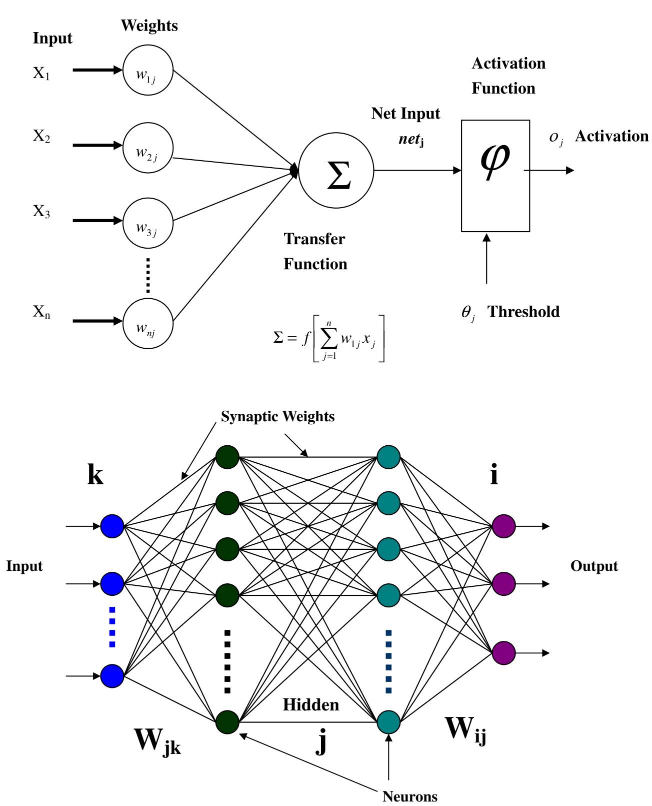

Fig. 3. Neural network general neuron and classification model.

5. Error back-propagation algorithm for WSNs

We consider a multilayer perceptron with three layers (input, hidden, output) as shown in Fig. 3. The connection weights between the jth neuron in the hidden layer and the kth neuron in the input layer is denoted by w_{jk}. Similarly the connection weights between the ith neuron in the output layer and the jth neuron in the hidden layer is denoted by W_{jk}. The sigmoidal response function used is

$$f_B(u) = \frac{1}{1 + \exp(-2\beta u)} \tag{1}$$

Our network receives a 1×24 input vector $X = \{x_k\};\ k = 1, 2, \ldots, 24$ representing a 16×16 pixel array of a handwritten digit.

The activation u_j of the jth neuron in the hidden layer is

$$u_j = \sum_{k=1}^{k} w_{jk} x_k \tag{2}$$

The output h_j of the jth neuron in the hidden layer is

$$h_f = f_B(u_j) = \frac{1}{1 + \exp(-2\beta u_j)} \tag{3}$$

Similarly the activation υ_i of the ith neuron in the output layer is

$$\upsilon_i = \sum_{j=1}^{J} W_{ij} h_j \tag{4}$$

and the output O_i of the ith neuron in the output layer is

$$O_i = f_B(\upsilon_i) = \frac{1}{1 + \exp(-2\beta \upsilon_i)} \tag{5}$$

The error between the actual output O and the desired output Y is calculated as follows:

$$E(w) = \frac{1}{2} \sum_{a,j} \left(y_i^{(\alpha)} - o_i^{(\alpha)} \right)^2 \tag{6}$$

We train the network to minimize the error E over the training set of 100 examples. Next, we perform the error back propagation algorithm as follows:

(I) Start with random weights.
(II) A training vector is applied to the input. The state of the hidden neurons is determined and then propagated to the output layer where the states O are determined.
(III) We calculate the error from between the actual output and the desired output and modify the weight matrices as follows:

$$\Delta W_{ij} = -\eta \frac{\partial E}{\partial W_{ij}} = \eta (y_i - o_i) f_i'(\upsilon_i) h_j \tag{7}$$

$$\Delta w_{ij} = -\eta f_j'(u_j) x_k \sum_q \delta_q W_{qj} = \eta f_j'(u_j) x_k \sum_q \left(y_q - o_q f_q'(\upsilon_q) w_{qj} \right) \tag{8}$$

(IV) Another training vector X_2 is applied to the network and steps II–III are repeated.
(V) Steps II–IV are repeated for all training vectors.
(VI) Steps II–V are repeated until the total error E is below a chosen threshold.

The resulting output node with the highest activation is interpreted as the perceived digit. Error back-propagation was used to train the neural network on a training set of 100 digits. The trained network was then tested on a separate set of 20 digits. Some of the parameters explored in the neural network implementation were learning rate, momentum parameter, and training iterations.

6. Parallel data fusion network in recognition and classification

Depending on the sensor network topology, it may be more useful to implement the distributed detection or estimation using a tree structure. Tsistsiklis (1993) shows that the optimal decision rules are still in the form of threshold tests. Tang, Pattipati, and Kleinman (1993) consider the case where the local decisions made at a number of sensors are communicated to multiple root nodes for data fusion. In the cases discussed above, the information flows in one direction from the sensors to either the single fusion center or to a number of root nodes. Even in the decentralized market topology, where numerous sensors report to multiple intermediate nodes, the graph of the network is still acyclic. If the communication network is able to handle the increased load, performance can be improved through the use of decision feedback (Alhakeem & Varshney, 1996; Pados, Halford, Kazakos, & Papantoni-Kazakos, 1995). Pados et al. (1995) examine two distributed structures: (1) a network where the fusion center provides decision feedback connections to each of the sensor nodes, and (2) a set of sensors that are fully interconnected via decision feedback. The performance of the fully connected network is quantifiably better, but their initial system was non-robust to variations in the statistical descriptions of the two hypotheses. Robust testing functions are able to overcome this problem, and they show that robust networks tend to reject the feedback when operating with contaminated data. Alhakeem and Varshney (1996) study a distributed detection system with feedback and memory. That is, each sensor not only uses its present input and the previous fed-back decision from the fusion center, but it also uses its own previous inputs. They derive the optimal fusion rule and local decision rules, and they show that the probability of error in a Bayesian formulation goes to zero asymptotically. Additionally, they address the communication requirements by developing two data transmission protocols that reduce the number of messages sent among the nodes.

Swaszek and Willet propose a more extensive feedback approach that they denote parleying (Swaszek & Willett, 1995). The basic idea is that each sensor makes an initial binary decision that is then distributed to all the other sensors. The goal is to achieve a consensus on the given hypothesis through multiple iterations. They develop two versions of the algorithm; the first is a greedy approach that achieves fast convergence at the expense of performance. The nth-root approach constrains the consensus to be optimum in that it would match that of a centralized processor having access to all the data. The main issue is the number of parleys (iterations) required to reach this consensus (see Fig. 4).

We examine two particular applications of sensor networks in the context of EMS in this paper:

1. Use of BPN to assist the optimal use of temperature, humidity, ultraviolet, and illumination four variable measurements for EMS.
2. Use of evolutionary algorithms to identify and classification the parameters for a control system.

Each intelligent sensor suite consisting of multiple sensors in the overall sensor network is capable of making some decisions based on its own inputs. These decisions are passed on to higher-level nodes in the control hierarchy for information assimilation or information fusion. These decision-making problems can be formulated as hypothesis testing problems in a distributed framework. For optimum results, environmental conditions must be

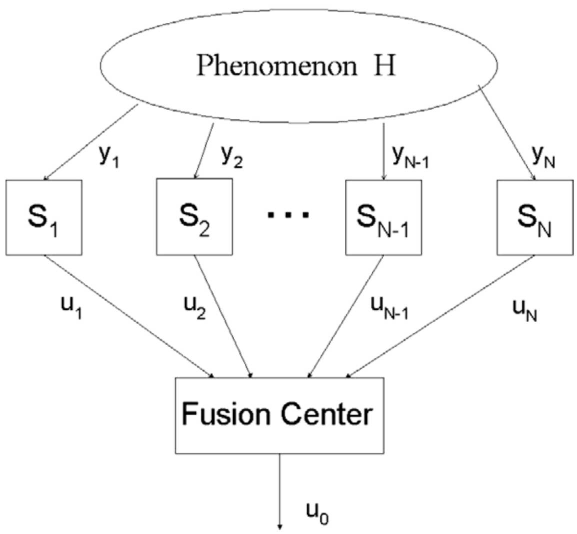

Fig. 4. Parallel data fusion network for multi-sensors.

optimized for each and every occupied space based on its particular environmental forcing parameters (e.g., emissions, intensity of light, occupant loads) and the needs of its occupants. The higher fidelity and better resolution information available from a sensor-rich environment will be processed and employed for optimal distributed control. We propose the use of neural networks and evolutionary algorithms to address some of these problems.

6.1. Design of fusion rules

Input to the fusion center: $u_i,\ i = 1, 2, \ldots, n$

$$u_i = \begin{cases} 0, & \text{if detector } i \text{ idecides } \mathrm{H}_0 \\ 1, & \text{if detector } i \text{ idecides } \mathrm{H}_1 \end{cases} \tag{9}$$

Input to the fusion center: u_0

$$u_0 = \begin{cases} 0, & \text{if } \mathrm{H}_0 \text{ is idecided} \\ 1, & \text{otherwise} \end{cases} \tag{10}$$

Fusion rule: logical function with N binary inputs and one binary output, the number of fusion rules is 2^{2^N}.

The possible fusion rules for two binary decisions based on BPN training process. Therefore, the optimum fusion rule that minimizes the probability of error is:

$$\sum_{j=1}^{N}\left[u_i \log\frac{1-P_{Mi}}{P_{Fi}} + (1-u_i)\log\frac{P_{Mi}}{1-_{Fi}}\right] \begin{array}{c} u_0 = 1 \\ > \\ < \\ u_0 = 0 \end{array} \log\eta \tag{11}$$

7. Sensor data estimation using neural networks

This section discusses the estimation of temperature, humidity, ultraviolet, and illumination four variable measurements in one region of a multi-zone environment using sensor readings obtained elsewhere, with BPN trained for the estimation task. This methodology can be employed for sensors that measure other environmental attributes for data fusion application. Example applications of the problem considered here include:

1. Monitoring large areas using a relatively small number of sensors.
2. Sampling sensors infrequently to save power and communication resources.
3. Being able to operate the control system effectively even when some sensors nodes fail or lose battery power.
4. Detecting possible failures in some sensors nodes using the readings of other sensors and coordinator.

7.1. Data collection

We used a simple experimental test, in which 24 wireless nodes, capable of measuring the intensity of temperature, humidity, ultraviolet, and illumination, were placed in each observational point where our campus. Every node point comprises four sensors and a network router. Among four sensors, the fusion center is responsible for analyzing the collected sensing data. These data from these 96 sensors were collected under varying outdoor or indoor environmental conditions, e.g., closing the window blinds, switching off some lights, and at various times of the day. The data collected from the six sensors are shown in Fig. 5. As the numbers of data points are relatively heavy, these data points were duplicated and some noise added to them, to increase the robustness of the training algorithm by BPN.

The intensity of four type sensors values in the different factory region are different due to different window blind settings, light status and shadowing. Moreover, these values change dynamically with different indoor and outdoor environmental changes, e.g., operating a light switch, changing window blind settings, or changing outside light intensity. Since any such change in environmental conditions affects the readings of multiple sensors, we expect that a neural network can be trained to estimate readings at multiple locations based on the observation of a single sensor node.

A one-hidden layer feed forward neural network with sigmoidal node transfer units is the prime candidate for experimentation, since such networks have been frequently used in other function approximation tasks. We also hypothesize that the hidden nodes in such a network compute features describing environmental conditions, essential to the estimation of light intensities at multiple locations; hence the same hidden nodes can be connected to different output nodes to estimate the readings of multiple sensors. Hence a BPN was applied to estimate the values of three sensors based on the readings of a single sensor (see Fig. 6).

The results obtained show that the BPN successfully estimates the intensity of temperature, humidity, ultraviolet, and illumination at three neighboring points based on the intensity at a single point. Estimation accuracy decreases with increasing differences between the environmental conditions at the reference point and at the estimated point.

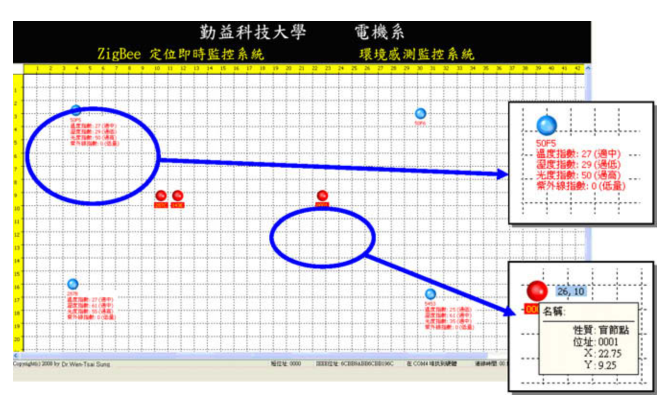

Fig. 5. Experiments result in EMS (estimated place: Yang-Fen Automation Electrical Engineering Company at Taichung Factory).

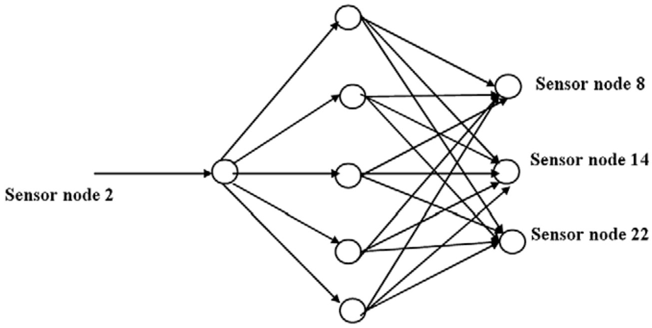

Fig. 6. BPN for estimation of the intensities at neighboring points.

7.2. Data fusion

Estimations made using a combination of readings from multiple sensors are expected to result in increased success. For this particular application, our simulation results showed that a data fusion model, implemented using a single monolithic BPN module with inputs from multiple sensors, was much less successful than a decision data fusion model in which the estimations made using single sensors are combined using a simple fusion rule, as shown in Fig. 7. The absolute error on the training data was 0.04 and the average mean absolute error on the test data was 0.018 after training for 400 h, demonstrating that decision fusion using BPN modules can give a very good estimate of temperature, humidity, ultraviolet, and illumination intensity values (see Fig. 8).

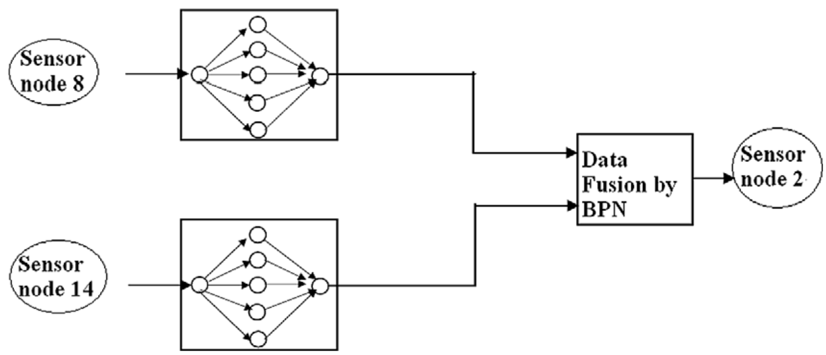

Fig. 7. BPN based decision data fusion model for estimation of the intensity of light at a single point based on the intensities at neighboring points.

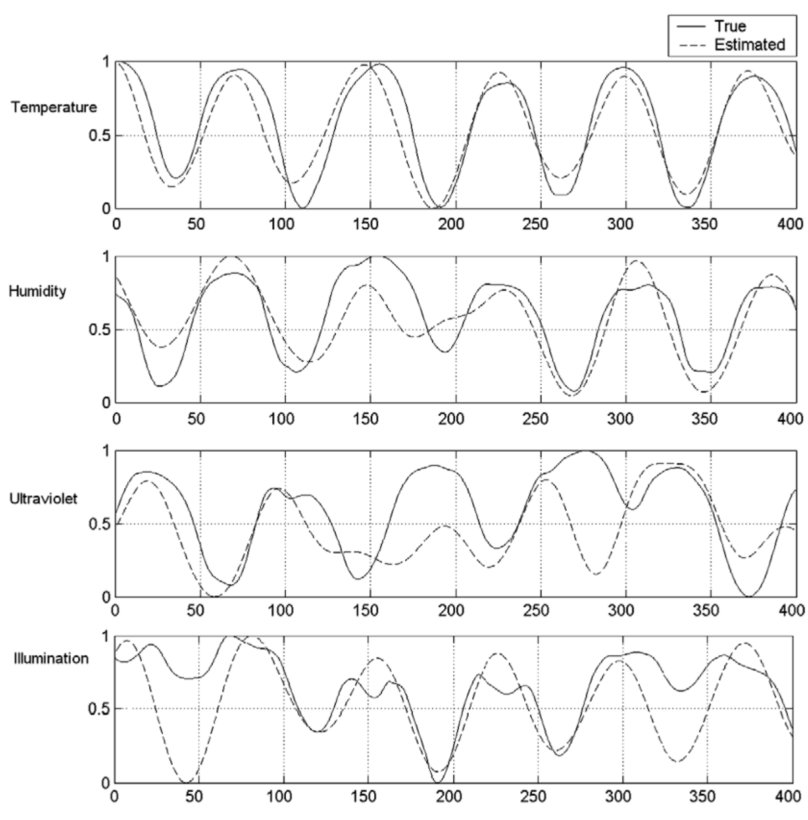

Fig. 8. Results using the data fusion approach: actual vs. estimated values. (Note: Ninety-six sensors (four type sensors) for real-time data fusion with recognition and classification process via BPN. (Estimated time is 400 h.))

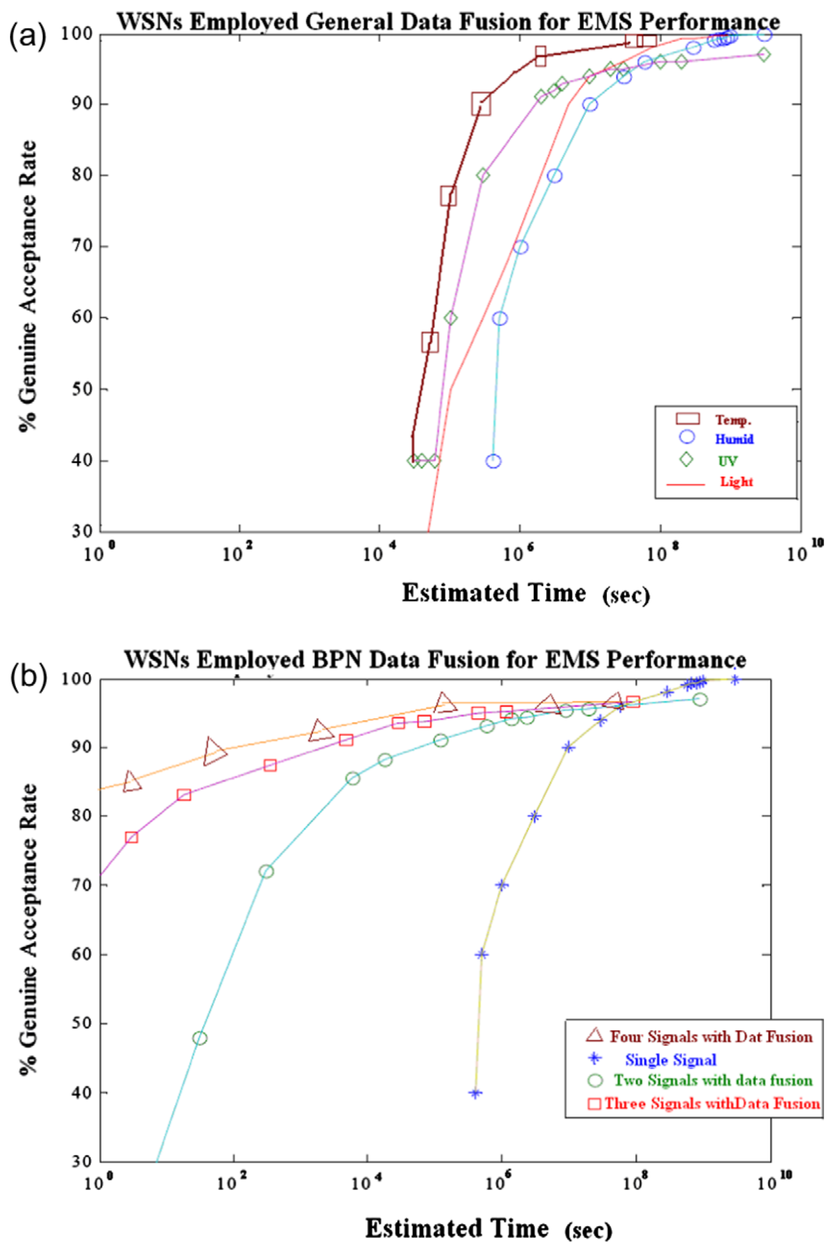

Fig. 9. Results of traditional data fusion methods compare with innovative BPN methods.

7.3. Performance improvement due to fusion

The WSNs was simulated with four category data from each node and the results for each of the different test conditions for temperature, humidity, ultraviolet, and illumination are given in Fig. 9a and b, respectively. Fig. 9a is non-data fusion process and Fig. 9b indicated it have data fusion process. Traditional data fusion methods compare with innovative BPN methods, the conspicuous distinction is data fusion genuine acceptance rate of the initial stage. This investigates employed BPN with training and learning ability that has improved the data fusion efficient for EMS based on ZigBee WSNs platform. Fig. 10 indicated ZigBee WSNs' Packages analysis and monitoring in this case study refer to our researches (Sung & Chung, 2008).

8. Conclusions

Sensor networks involve technologies from three related areas: sensing, communication, and computation (hardware, software, and algorithm). Lately a lot of research work has been done in all of these fields to make sensor nodes more intelligent and useful. Wireless sensor networks have emerged as a new information-gathering paradigm based on the collaborative effort of a large number of sensing nodes. This study discusses the classification and fusion approach in WSNs, which BPN based feature extraction method is proposed. This method partitions the frequency band in different resolution to distinguish the difference in low-frequency band and reduces the feature dimensions greatly. The extracted feature expresses stable classification rate for different moving condition. Due to the multiresolution property of wavelet decomposition cannot only eliminate unstable variety of frequency feature, but also merge discrepancies. Therefore, weighted BPN classification rule uses the distance of feature *x* and its nearest neighbors to denote the degree committing to each class. This can provide more information of *x* and its neighbors than that of voting BPN rule and keeps the merits of non-parametric and easy to use.

In this study, we design four various sensors in a circuit board which aggregated temperature, humidity, ultraviolet, and illumi-

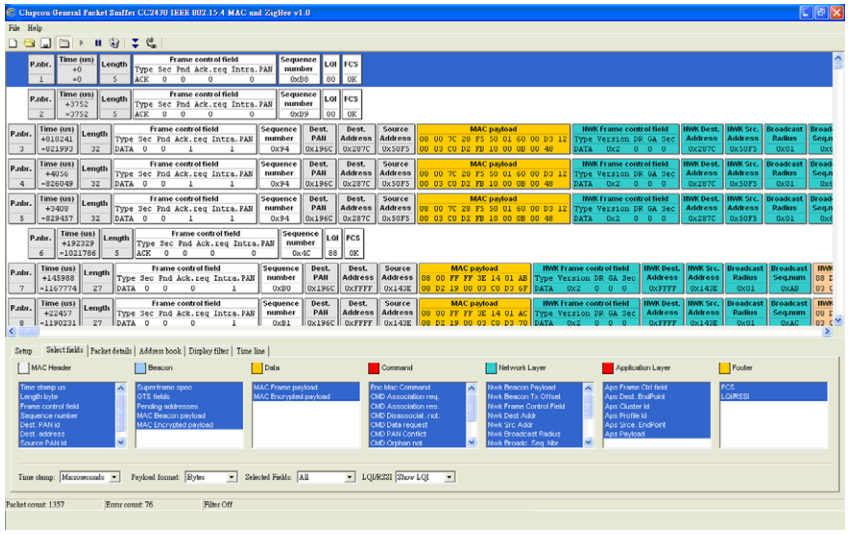

Fig. 10. The ZigBee network packages analysis and monitoring.

nation measurements for EMS around at the same time. Our primary network architecture consists of 24 nodes and beacon behavior in real-time mode with interval about 0.5 s. Multilayer perceptrons BPN have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the back-propagation algorithm. This algorithm is based on the error correcting learning rule. Finally, the sink nodes would process various signal sources for data fusion in recognition and classification via BPN technology.

Acknowledgements

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