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Advanced Bio-Inspired Plausibility Checking in a Wireless Sensor Network Using Neuro-Immune Systems

Autonomous Fault Diagnosis in an Intelligent Transportation System

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***Abstract*—Recent developments in wireless sensing technology lead to implement advanced algorithms for distributed data processing in various applications; intelligent transportation system is one of the main applications of the advanced networked sensing technology to monitor the environmental conditions for controlling the quality of the products. To ensure the desired performance of a wireless sensor network, the reliability of the network records needs to be evaluated using an efficient data processing algorithm. In this paper, a new application of a bio-inspired technique is introduced for autonomous plausibility checking in a wireless sensor network; at first, an optimized Neuro-immune system is introduced and developed to predict the sensor records; then, performance of the proposed Neuro-immune system is compared with a neural network approximation mechanism. A secondary algorithm evaluates the sensor records to check the plausibility of the records in the wireless sensor network. The proposed data processing algorithm could serve in various applications of wireless sensor networks.**

Keywords-wireless sensor network; distributed data processing; artificial immune system; artificial neural network.

I. INTRODUCTION

Due to recent developments in networked sensing technology, wireless sensor networks are becoming more widely used to control and monitor the environmental conditions in various applications like transportation systems. A sensor network includes many smart devices to perform a required task depending on type and capability of the sensor nodes [1]. Different architectures could be established to design a sensor network either in a centralized or a decentralized manner; the required decisions could be locally made in different layers of a wireless sensor network. In each interconnected sensor network, it is necessary to evaluate the reliability of the sensor nodes by processing the recorded data of each node as well as each cluster.

In general, plausibility of a wireless sensor network denotes the ability of the system to correctly record and make the appropriate decisions adhering to desired environmental conditions to perform a required task. The plausibility could be affected by undesired events (like faults) which lead to any unwanted deviation of sensor network records. There are different techniques to evaluate the performance of the wireless nodes including modern and classical techniques [2]; artificial neural network (ANN) is a knowledge based technique including nonlinear mapping features and generalization which makes it favorite for model-free data processing [3]. An optimized neural network was implemented on a wireless sensor network to approximate and classify the records for plausibility checking [4]. The advantages and disadvantages were highlighted in comparison with the classical approaches (like Least Squares) [5][6]. Artificial immune system features, which are established on human biological immune system to detect and eliminate the threats, could be integrated with different techniques like neural networks to increase the flexibility and accuracy of data processing [7].

In this paper, a wireless sensor network is used to record the environmental parameters including temperature by imote2 sensor nodes. A novel bio-inspired technique for autonomous plausibility checking is introduced and implemented. The proposed optimized bio-inspired technique could serve in various applications of wireless sensor networks.

Related works are studied in Section II; then, the concept of autonomous plausibility checking in a wireless sensor network is described in Section III. The idea of Neuro-immune system is discussed to design the data processing mechanism in Section IV; finally, the experimental results using the proposed data processing technique is presented.

II. RELATED WORK

Distributed data processing could be used for any local decision making like power saving or routing in a wireless sensor network to increase the overall performance [8][9]. Thus, accuracy and energy efficiency of the chosen data processing technique are taken into consideration [10]. Data processing architecture consists of two main architectures including data approximation and classification. Data approximation is established on either linear or nonlinear mapping of various data; then, the approximated data could be used either for data fusion purposes [4]. To approximate the records in a wireless sensor network, neural network

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could be an appropriate choice due to its' nonlinear mapping features, preferable to linear approaches like Least squares. Also, depending on the application, different neural networks are employed to use in data classification [3]. Artificial immune system is another bio-inspired technique which could be combined with neural network for optimization. Dasgupta compared artificial neural network with immune systems [11]. De Castro and Von Zuben performed comparative studies about artificial immune system and neural network [12]. They developed a growing Boolean competitive network using immune system features including competitive learning characteristics. Initializing weights of the multilayer feedforward neural networks was another attempt to combine a neural network with immune system [13]. This approach leads the neural network to converge to a local optima which improves the performance of the network in some applications.

Considering the recent efforts in designing the neuro-immune systems to design the optimized neural networks, a novel bio-inspired data processing technique is introduced in this paper to check the plausibility of the records in a wireless sensor network; the experimental results are used to compare the accuracy of an optimized backpropagation technique with the proposed neuro-immune system.

III. AUTONOMOUS PLAUSIBILITY CHECKING IN WIRELESS SENSOR NETWORKS

Many sensor nodes are used in a wireless sensor network to monitor the environmental conditions in a transportation system. It is necessary to evaluate the reliability of the records to keep the quality of the products high during transportation. Any abnormality in a wireless sensor network is detected, isolated and investigated in an autonomous wireless sensor network. Some decisions are made locally to evaluate the records of each cluster.

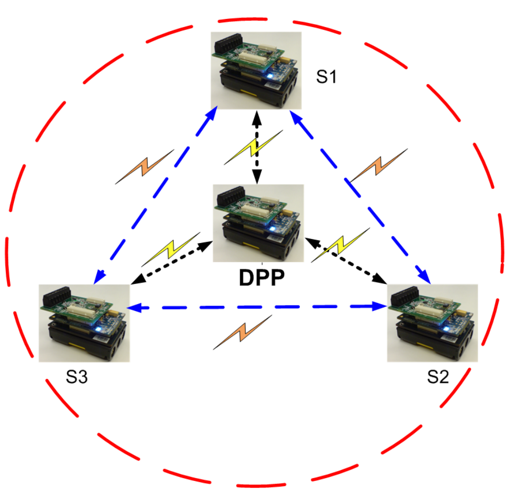

Figure 1. Local Data processing at a cluster in a wireless sensor network.

Figure 1 shows a cluster of a wireless sensor network including imote2 sensor nodes; data are sent and received via Imote2's CC2420 radio, with a processing frequency of 104 MHz (in this research) at RF power of -10 dBm for all tests [14]. A data processing platform observes the sensor records at each cluster to make an appropriate decision when one of the sensor nodes deviates from desired behavior. Each cluster is monitored using a local data processing platform (DPP) and the reliability of each group of data processing platforms is evaluated using a global DPP.

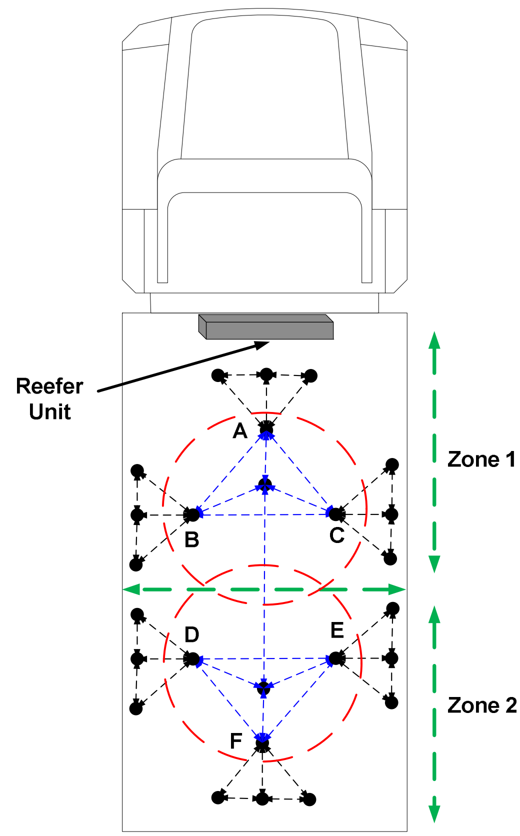

Figure 2. Local and Global data processing architectures.

Figure 2 illustrates the generalized data processing architecture inside a truck; according to this figure, each three sensor nodes are observed by a local data processing platform in each zone. Then, the records of the local data processing platforms (A, B, and C in zone 1 and D, E, and F in zone 2) are processed together to detect any abnormality in the sensor network. A reefer unit establishes the desired environmental conditions by cooling down or warming up the truck. Figure 3 shows a two stage data processing platform including a knowledge based data approximation as well as a classification mechanism. To perform data processing at each cluster either locally or globally, the sensor records are approximated by the Neuro-immune system. Approximated data are compared to the actual records of the under approximation nodes by generating so-called approximation residuals.

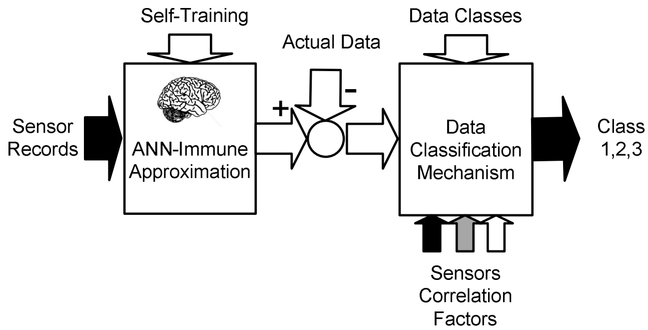

Figure 3. Bio-inspired data processing in a wireless sensor network.

At second step, the reliability of the records is evaluated using a classification algorithm to detect any abnormality in the wireless sensor network. Sliding correlation factor of the sensor nodes in each cluster is a complementary condition to classify the records. The Neuro-immune system data processing architecture is introduced in next section for data approximation and classification in a wireless sensor network.

IV. NEURO-IMMUNE SYSTEM DESIGN

The artificial immune system is derived from human biological immune system to defend the body against the threats. Remembering the past encounters and recognition features are the main specifications of the artificial immune systems [7]. The Biological immune system protects the human body from infection using primary response to invading pathogens as well as a secondary response to remember past encounters. Antibodies (Ab) and Antigens (Ag) are two types of molecules; Ab molecules (cell receptors) bind to Ag (pathogenic microorganisms) for their posterior elimination. The Ab and Ag participate in immune recognition between the binding region of the receptor and epitope [7].

For representing the artificial immune systems, the antibody and antigen vectors are shown as:

$$Ab = \langle Ab_1, Ab_2, ..., Ab_L \rangle$$

$$Ag = \langle Ag_1, Ag_2, ..., Ag_L \rangle$$

Also, the affinity function which denotes the degree of match between the mentioned vectors could be described by either Euclidian or Manhattan distances;

$$D = \sqrt{\sum_{i=1}^{L} (Ab_i - Ag_i)^2} \quad \text{(Euclidian distance)} \qquad (1)$$

$$D = \sum_{i=1}^{L} |Ab_i - Ag_i| \quad \text{(Manhattan distance)} \qquad (2)$$

In this paper, immune system is used to design an optimized neural network to improve the data processing in a wireless sensor network. The Neuro-immune system deals with the training weights and input set to train the network.

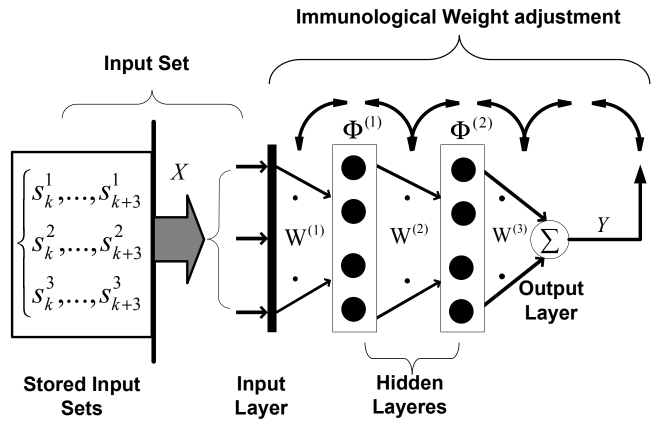

Figure 4. Proposed Neuro-immune architecture.

Figure 4 shows the proposed Neuro-immune architecture; to design the network, different parameters have been explored (such as number of layers and neurons) in order to obtain the Maximum data approximation accuracy when the temperature of a sensor is approximated using three neighboring sensor nodes at each cluster [4][6]. Two hidden layers are selected each including four neurons with sigmoidal activation functions ($\Phi^{(1)}$ and $\Phi^{(2)}$); the network layers are connected using the weight vectors ($W^{(1)}$, $W^{(2)}$, and $W^{(3)}$). Each weight vector at each layer (i) includes some weight elements;

$$W^{(i)} = \left[w_1^{(i)}, w_2^{(i)}, w_3^{(i)}, w_4^{(i)} \right]$$
$$i = 1,2,3$$

A. *Sliding Backpropagation*

Sliding backpropagation was developed using the last sequential records of all sensor nodes at each cluster; to approximate the records of each under approximation sensor node, the neural network is trained using the records of the neighboring sensor nodes [4]. There are four sensor nodes at each cluster, one as a data processing platform, to monitor the cluster; to predict new values of each under approximation sensor node, last four sequential records of the neighboring sensor nodes are assumed as the approximation parameters (as training input); they are mapped into the last four sequential records of the under approximation sensor node (as training target) to train the neural network. For example, to approximate the records of s_{k+4}^1 (at instance $k+4$), last four sequential records of the neighboring sensors are collected as the approximation parameters (s^2, s^3 and s^{DPP}) at instances k, $k+1$, $k+2$, and $k+3$;

$$X = \begin{bmatrix} s_k^2 & . & . & s_{k+3}^2 \\ s_k^3 & . & . & s_{k+3}^3 \\ s_k^{DPP} & . & . & s_{k+3}^{DPP} \end{bmatrix} \quad \text{(Training input)}$$

The target vector denotes the last four sequential records of the under approximation node which is s^1 in this example.

$$Y = \begin{bmatrix} s_k^1 & s_{k+1}^1 & s_{k+2}^1 & s_{k+3}^1 \end{bmatrix} \quad \text{(Training target)}$$

In sliding backpropagation algorithm, the initial weights are chosen randomly; then, the weights are updated using the "gradient descent" algorithm to minimize the error function (Er) between the desired and actual outputs of the network during the training phase [4].

$$\mathrm{Er} = \frac{1}{2}\sum [\mathrm{D}^1 - \mathrm{Y}^1]^2 \qquad (3)$$

In (3), D^1 and Y^1 refer to the desired and actual outputs of s^1, respectively. The weight variations are proportional to the negative gradients of the error function and current weights where η is the learning rate in (4);

$$\Delta \mathrm{W}^{(3)} = -\eta \nabla \mathrm{W}^{(3)} \mathrm{Er} \qquad (4)$$

Also, the weight vectors are consequently updated according to the negative gradients of the error function at each instance (k') by (5).

$$\begin{aligned} &\mathrm{W}^{(i)}(\mathrm{k}'+1) = \mathrm{W}^{(i)}(\mathrm{k}') + \Delta \mathrm{W}^{(i)} \\ &i = 1,2,3 \end{aligned} \qquad (5)$$

After training, by feeding new values of the approximation parameters, the new record of the under approximation node is predicted. This procedure is applied to predict the records of each node in similar way.

B. Neuro-Immune System

Basically, adjusting the weights has major impact on the quality and speed of the data approximation using neural networks. Adhering to insufficient local minima which leads to inadequate data approximation is a big problem in training the neural networks [15]. For this purpose, immune system is implemented to initialize the weights at each layer of the network. The developed approach is based on a simulated annealing algorithm (de Castro et al) [13]. This approach generates a set of weight vectors to reduce the likelihood of the network to converge to a local optima. The simulated annealing (SA) technique is derived from atomic displacement in liquids; the atomic position in a given liquid sample is calculated by a probability factor where E and T are the configuration energy and temperature.

$$P(\Delta E) = \exp\left(\frac{-\Delta E}{T}\right) \qquad (6)$$

Each atomic displacement leads to an energy change (ΔE); when the energy change is positive, probability of accepting the atomic displacement is calculated by (6) [13]. To define the energy function in a data approximation architecture, Euclidean distance (Dis) is used to check the affinity of the weight vectors in (7);

$$Dis(w_i, w_j) = \sqrt{\sum_{k=1}^{4} (w_{ik} - w_{jk})^2} \qquad (7)$$

Where w_i, w_j are the connected weight vectors to different neurons in a layer. The energy is defined as the sum of the Euclidean distances among all weight vectors (antibodies). This energy is minimized to adjust the network weights by (8); thus, the weights are selected by the immune system to generate the distributed vectors instead of being initialized randomly.

$$E = \sum_{i=1}^{4} \sum_{j=i+1}^{4} (w_i, w_j) \qquad (8)$$

Another contribution of the immune system is to observe and deal with the input set to train the neural network. As mentioned before, the accuracy of the sliding backpropagation is highly dependant on the last four sequential records of each sensor node; sometimes due to the inaccurate readings of the sensors, the difference between the approximation and the actual value, which is called approximation residual, increases. As in the sliding backpropagation technique, only the four sequential records at k, $k+1$, $k+2$, and $k+3$ are taken into account for data approximation at $k+4$, the inaccurate readings will lead to inaccurate data approximations for the next sequential approximations. The other case is when the sensor records are not plausible due to fault occurrences; therefore, it's necessary to remove the inaccurate or faulty sensor readings from input set for the next data approximations. For this purpose, the immune system is utilized; at each instance (t), last eight sequential records (as antibodies) and the resultant approximations (as antigens) (at t-8,…,t-2, and t-1) are stored. The Euclidean distance between the last eight approximations and related actual values are calculated and the trend of data approximation is observed. When the Euclidean distance increases considerably, it shows that sensor records are not accurate enough to be involved in the new training set. Therefore, the inaccurate or faulty records are not longer taken into account to generate the new input set for next approximations. The proposed neuro-immune algorithm is described briefly in Figure 5.

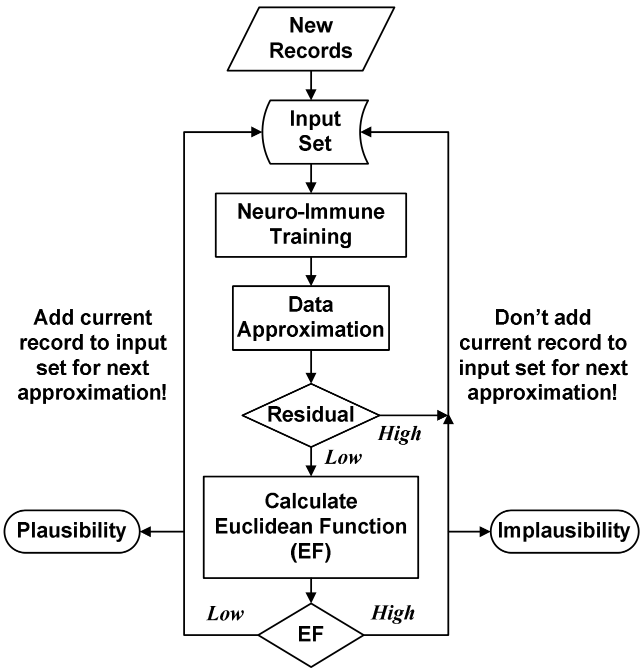

Figure 5. Neuro-immune system for plausibility checking.

At first, the last four sequential records are used to generate the input set. The Neuro-immune system adjusts the weights and after data approximation, the residuals are generated. If the residual value is high, the inaccurate records won't be involved in the new input set for the next data approximation; otherwise, by calculating the Euclidean function, the plausibility of records is investigated; this issue as well as the "high" and "low" terms will be further explained in the following section.

V. Experimental Results

The proposed neuro-immune algorithm was implemented on a wireless sensor network including Imote2 sensor nodes [14] to record and process data for plausibility checking. The reefer unit could cool down or warm up the truck according to the set points; some arbitrary set points are used to test the performance of the proposed mechanism to establish the transportation condition. The chosen reefer unit set points are 14, 8, 12, 6, and 10°C respectively, each takes 60 minutes; therefore, the test duration is 300 minutes. The average ambient temperature is about 18.3°C. All temperature records in different positions are affected by the reefer temperature. According to the Figure 2, two main zones are considered for local and global data processing. To examine the proposed Neuro-immune algorithm, the records of the sensors A, B, and C are processed at Zone 1 as well as nodes D, E, and F which are local data processing platforms at zone 2. At first, the neural network (ANN) was implemented to approximate the records at zone1 (for nodes A, B, and C) by the sliding backpropagation which uses the last four sequential records to train the network [4].

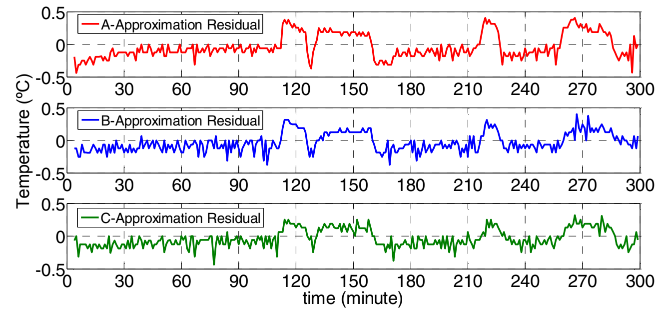

Figure 6. Approximation residuals using the sliding backpropagation.

The approximation residuals which are the instantaneous differences between data approximations and the actual records are seen in Figure 6. The results show that ANN approximation residual lays within ±0.5 °C when the accuracy of the data approximation at each instance is highly dependant on the last four sequential records of each sensor node. The calculated approximation residual using the Neuro-immune system is illustrated in Figure 7. The results show that the Neuro-immune system produces less approximation residual in comparison to the sliding backpropagation network (±0.3 °C).

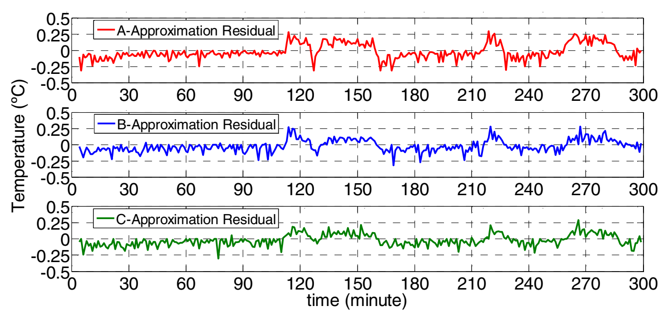

Figure 7. Approximation residuals using the Neuro-immune system.

For a more precise comparison, the average of the calculated approximation residual is presented in Figure 8 at zone 1; it compares the average approximation residual of nodes A, B, and C using the sliding backpropagation (ANN) and Neuro-immune system.

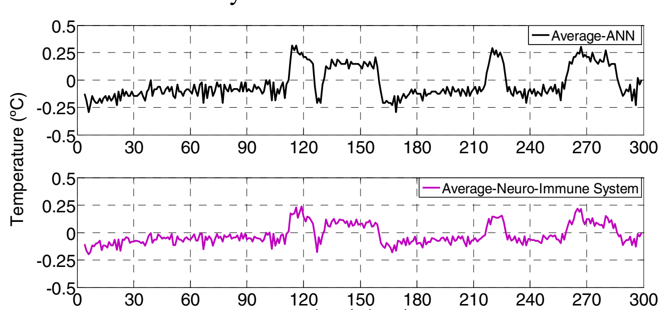

Figure 8. Average approximation residual using sliding backpropagation (ANN) vs. Neuro-Immune system at zone 1 (A, B, and C)

Also, the "root mean squared errors" (RMSE) of the approximations are calculated;

$$RMSE(Y_{App.}) = \sqrt{\frac{\sum_{i=1}^{n}(Y_{Actual} - Y_{App.})^2}{n}} \qquad (9)$$

In (9), Y_{Actual} and $Y_{App.}$ are the actual and approximated values which are assigned to the instantaneous temperature values of each under approximation node; n denotes the number of the approximated records. The RMSE of the average approximation residual using ANN and Neuro-Immune system is illustrated in Figure 9. Considering the Figure 9, the Neuro-immune system leads to more accurate approximation in comparison to the sliding backpropagation.

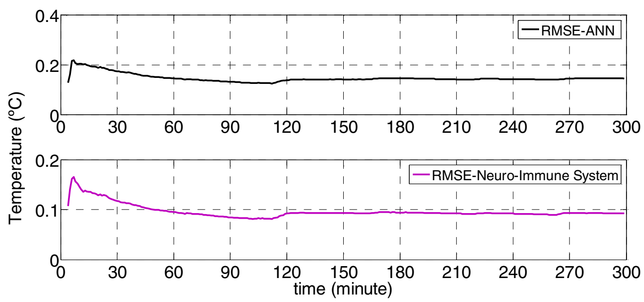

Figure 9. RMSE of data approximation in zone 1.

The RMSE of the average approximation residual for each cluster increases during the first minutes of data approximation, and afterward remains mostly steady due to the nature of the RMSE function. During the test, the RMSE of the average approximation residual in zone 1 (including nodes A, B, and C) reaches to about 0.145 and 0.092 (ºC) using the sliding backpropagation and Neuro-immune systems, respectively; the RMSE value for zone 2 (including nodes D, E, and F) reaches to 0.166 and 0.104 (ºC) using the proposed algorithms respectively, as seen in Figure 10.

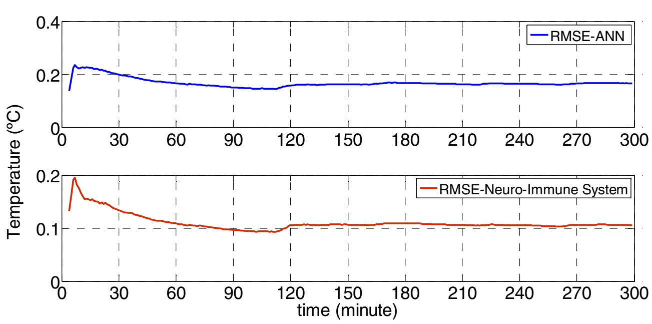

Figure 10. RMSE of data approximation in zone 2.

Table I compares the accuracy of the neuro-immune algorithm and sliding back propagation. The results show that despite increasing the calculation time for about 0.5 Sec., the Neuro-immune data approximation is more accurate than ANN. The proposed scenario was tested in 5 different environmental conditions by adjusting the reefer unit using the arbitrary set points including [10ºC, 20ºC], [0ºC, 10ºC], [-10ºC, 10ºC], [0ºC, 20ºC], and [-10ºC, 0ºC]; the accuracy of the proposed Neuro-immune system was higher than sliding backpropagation in all cases.

TABLE I. COMPARISON OF DATA APPROXIMATION TECHNIQUES

Data Approximation	Accuracy (ºC)	Average Calculation Time
Sliding Backpropagation	±0.5	2.3 Sec.
Neuro-immune System	±0.3	2.8 Sec.

The role of the classification mechanism is to use the approximation values to classify the records as plausible, implausible and unknown. To classify the records, after each data approximation, the immune system calculates the Euclidean distance between the actual records (Ab) and approximations (Ag) at each instance. Figure 11 shows the instantaneous calculated Euclidean functions in zone 1.

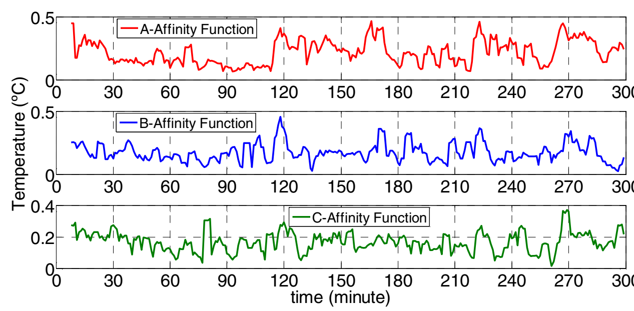

Figure 11. Euclidean distance between sensor nodes.

Figure 11 illustrates that the Euclidean function (*EF*) for each node remains less than 0.5 °C when the records of all three sensor nodes are plausible. Any deviation from this range could be classified as unknown or implausible (which was described before as "high" according to Figure 5). When there is a fault in the wireless sensor network (like defection or battery discharge), the records are assumed as implausible which causes a considerable deviation of data approximation from the actual records in the wireless sensor network. Sometimes due to inaccurate readings or weakness in data approximation the data is classified as unknown. The unknown area has to be investigated whether the deviation of data approximation from the actual value is due to a fault occurrence in the wireless sensor network or not. Three data classes are defined;

1. Class 1: Plausible records (*EF<0.5°C*).
2. Class 2: Unknown (plausible or implausible) (*0.5°C< EF<1°C*).
3. Class 3: implausible records (*1°C< EF)*.

To evaluate the unknown records (Class 2), an absolute sliding correlation function is calculated to determine the relationships between sensor records [4].

$$ASC(S_i, S_j) = \left| \frac{\sum (s_i - \bar{s}_i).(s_j - \bar{s}_j)}{\sqrt{(s_i - \bar{s}_i)^2 . \sum (s_j - \bar{s}_j)^2}} \right| \quad (10)$$

$ASC(S_i, S_j)$ denotes the absolute sliding correlation factor between S_i and S_j; also, s_i and s_j are the elements of those two sets respectively over the last four sequential records; $\bar{s}_i$ and $\bar{s}_j$ are their average values.

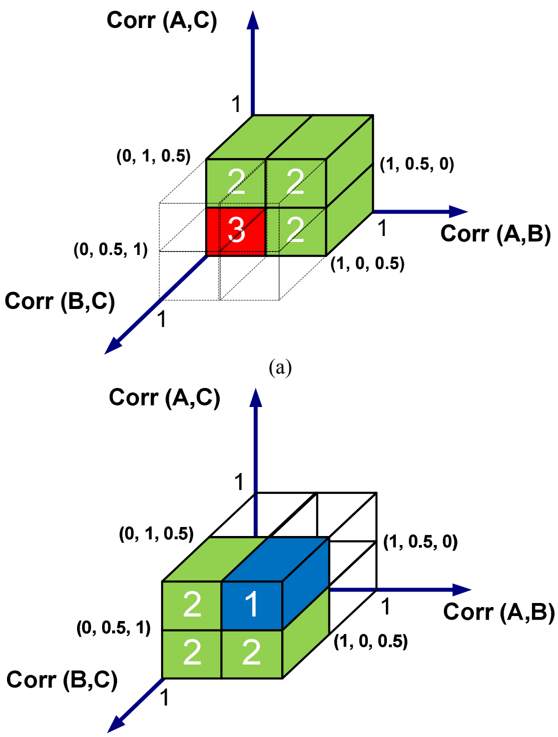

Figure 12. Data classification range.

According to Figure 12, when the absolute sliding correlation factors between sensors are high, the unknown class is assumed as plausible (Class 1); otherwise, when the EF is in unknown range and the sensor records are not highly correlated, the records is classified as implausible (Class 3).

VI. Conclusion

In this paper, an advanced bio-inspired data processing technique was presented for a wireless sensor network. The implemented technique consists of two stages including a Neuro-immune data approximation and a data classification mechanism. Immune system was used to train the neural network; the obtained results showed that the developed Neuro-immune approach leads to more accurate data approximation in comparison to the sliding backpropagation technique. To evaluate the reliability of the records in the wireless sensor network, the Euclidean distances were calculated. The future work is application of the immune system to optimize other network parameters such as number of neurons in order to improve the data processing accuracy.

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