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ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

Information fusion method of multichannel nanosensors based on neural network

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Abstract. Information fusion approaches have been commonly used in multi sensor environments for the fusion and grouping of data from various sensors which is used further to draw a meaningful interpretation of the data. Traditional information fusion methods have limitations such as high time complexity of fusion processes and poor recall rate. In this work, a new multi-channel nano sensor information fusion method based on a neural network has been designed. By analyzing the principles of information fusion methods, the back propagation based neural network (BP-NN) is devised in this work. Based on the design of the relevant algorithm flow, information is collected, processed, and normalized. Then the algorithm is trained, and output is generated to achieve the fusion of information based on multi-channel nano sensor. Moreover, an error function is utilized to reduce the fusion error. The results of the present study show that compared with the conventional methods, the proposed method has quicker fusion (integration of relevant data) and has a higher recall rate. The results indicate that this method has higher efficiency and reliability. The proposed method can be applied in many applications to integrate the data for further analysis and interpretations.

Key words: nanosensors; multiplexing; information fusion; data fusion; neural network.

1. INTRODUCTION

The fusion of information applies to data that has already been processed. Data fusion refers to various sources of information to be obtained. These techniques have been commonly used in multi-sensor environments to fuse and collect data from various sensors. Said methods are used in other areas as well, such as text processing. It aims is to reduce the likelihood of detection errors and to improve the reliability with data from multiple distributed sources by using information fusion in multi- sensor environments. Data fusion techniques are traditionally probabilistic fusion (e.g., Bayesian fusion), evidential belief reasoning fusion (e.g., theory of Dempster Shafer), and rough set fusion etc. New information fusion technologies with powerful data processing capabilities have been developed with the aid of sensors, smart hardware, and many other data processing methodologies. The efficiency of data fusion algorithms has been improved by machine learning algorithms.

The field of information fusion technology is a relatively young one in the field of information science. Several multi-sensor systems have emerged for fusion of multiple data, such as microelectronics, signal detection and processing techniques, computers, and network communications [1]. Multi-sensor information fusion technology has grabbed lot of attention in recent years. The term "multisource information fusion" refers to the gathering of data from multiple sources to draw inferences to conclude the relevant information. Information fusion approaches have been commonly used in multisensor environments for the fusion and grouping of data from various sensors. These techniques may also include areas such as text processing. The fusion of information in multisensor environments using data from multiple distributed sources is used to ensure lower likelihood and improved consistent detection errors.

The following groups are classified as information fusion: (i) the data association, (ii) the state estimate, and (iii) the decision fusion. This paper aims to illustrate the key stages of the process for information fusion design and provides an overview of the usual techniques used for framework construction.

1.1. Classification of information fusion approaches

The classification of information fusion approaches is dynamic and rigorous. There is a distribution of current methods and techniques as follows:

1. Based on the relationships between input data sources. These relationships can be (a) complementary, (b) redundant, or (c) cooperative information;
2. Based on the nature and properties of the data input/output;
3. Based on the abstraction of the levels of data to be defined as (a) coarse measurement, (b) signals, (c) features or decisions;
4. Based on the different levels of fusion; based on the architectures that can: (a) be centralized, (b) are decentralized, or (c), distribute;

1.1.1. Cataloging based on the relation between input data sources

The cataloging criteria proposed by Durrant–Whyte [2] were as described in Fig. 1 as:

1. Complementary: if different sections of the scene are shown in the information it helps in obtaining more global information from the sources of input.

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2. Redundant: When information about the same goal can be fused to increase trust is given by multiple sources.
3. Cooperative: Information is merged into a piece of complex information as compared to the original.

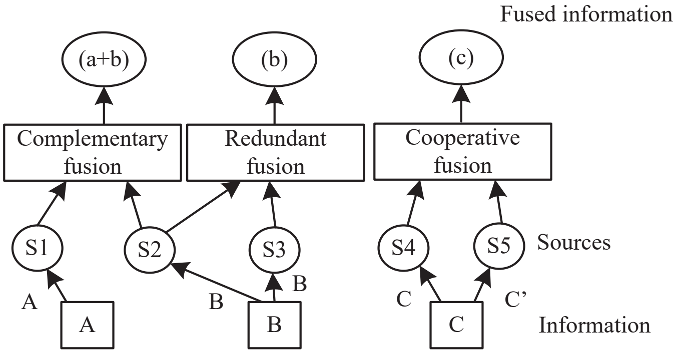

Fig. 1. Cataloging based on the relationship between data sources

1.1.2. Dasarathy's Classification

Dasarathy's [3] classification is considered to be one of the most popular classifications of information fusion. The information fusion otherwise known as data fusion is classified as shown in Fig. 2:

1. Data in-data out (DAI-DAO): It is the basic or elementary data fusion method. Inputs and outputs of the data fusion process are raw data that are more reliable or accurate. As soon as the data is gathered from the sensors fusion of data is done. Signal and image processing algorithms are employed at this process stage;
2. Data in-feature out (DAI-FEO): Raw data from the sources are used to extract features or characteristics that define an entity in the environment it is processing in this level;
3. Feature in-feature out (FEI-FEO): Input and output are both considered as features in this level of the data fusion process. This relates to a set of features that can be used to generate new features. This process is known as feature fusion, symbolic fusion, information fusion, or intermediate level fusion;

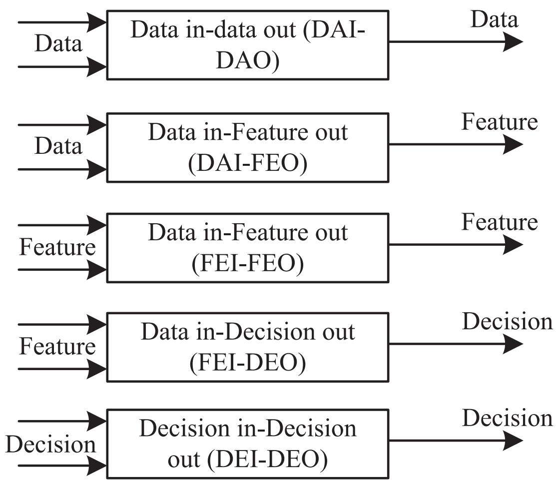

Fig. 2. Dasarathy's classification

4. Feature in-decision out (FEI-DEO): Set of features obtained are considered as input which generates decisions as output. Most decision-based classification system on a sensor's inputs fall belong to this category of classification;
5. Decision In-Decision Out (DEI-DEO): Decision the fusion helps in fusing of input decisions for improved and efficient decisions.

Various algorithms in machine learning are combined to reach better predictions than a single classification. Multiple device classification methods are advised to address complex issues, high dimensionality, and sensor data discrepancies. Therefore, the activity classification system improves precision, robustness, and widespread. For human activity identification and health tracking, typical multiple classifier device methods are used. These work on the random sampling of training data or various poor classification algorithms to construct an interconnected range of opinions through voting, dynamic decision-making rules, and the Dempster–Shafer theories.

Nanosensors are devices that convert the physical, chemical, or biological information of the object being monitored into detectable photoelectric signals using nano level materials. It is a "magnifying glass" for a human to spy on the microscopic world. The birth of nanosensors has accelerated the pace of human society towards the era of information and intelligent sensors. Compared with traditional sensors, nanosensors have excellent performance such as high sensitivity, multi-function, and high intelligence. They can be operated and controlled at the molecular level and provide an important diversified means for people to detect and perceive the microscopic world on the nanoscale sensitively. At the same time, nanosensors have the advantages of integration, array, miniature, intelligence, and portability, greatly expanding the application of sensors in medical diagnosis, environmental monitoring, wearable devices and other fields [4, 5].

The information network composed of multiple nanosensors is called a nanosensor network. In the nanosensor network, most of the traditional information collection methods are to achieve the purpose of monitoring targets and sensing the environment using multiple nanosensor nodes. However, this method of using a single node to transmit information to the sink node will result into a great amount of redundant information in the network, resulting in a waste of energy and resources. Moreover, in most nanosensor network environments, this original redundant information is not needed, which reduces the efficiency of information collection and fails to improve the timelines [6, 7].

In recent years, higher requirements have been put forward for information processing technology. In the complex multi-channel nanosensor network, the information shows the diversity of types, the super-large capacity, and the complexity of the relationship between the information. If the multi-channel data is not fully processed, it is difficult to achieve high precision, and high speed of data analysis and application. Therefore, in the information society, it is required to accurately and quickly fuse the multi-dimensional information collected from multi-channel nanosensors, and to generate efficient and reasonable fusion quickly; and then to make accurate estimations and decisions based on data fusion.

An attempt is made in designing a multi-sensor data fusion method based on interconnection probability weighting. Firstly, the single-sensor JPDA algorithm is presented, and then the multi-sensor JPDA mathematical model is introduced. Based on this model, parallel and sequential multisensor data fusion formulas are derived by using interconnection probability weighting [8]. A sensor data conflict measurement and fusion method based on weighted reliability entropy is designed. Firstly, the uncertain information contained in the identification framework (FOD) is integrated into the newly proposed Deng entropy model. Then, weighted Deng entropy is used to quantify the uncertainties in different sensor data sources. Finally, the sensor conflict data fusion and target recognition decision are realized [9].

After utilizing the traditional methods into practice, it is found that the fusion process is time-consuming, and the recall rate is high. To address this problem, a novel neural network-based information fusion method of multichannel nanosensors is developed and tested for the practical problems and found satisfactory. In BPNN, each layer's output is transferred in the next layer to its neurons. That is to say, BPNN can maintain a biassing neuron to generate constant inputs. The previous method involves BPNN creating a neural network close to the neural network by eliminating errors. To our knowledge, this is the first attempt in neural network-based information fusion method of multichannel nanosensors.

1.2. Major contributions of the research work

- First of all, a grouping of the prevailing approaches is performed, and their important design choices are presented.
- A novel information fusion method of multichannel nanosensors using BP-NN is designed.
- An experimental study is conducted to evaluate the results based on the existing benchmarked techniques.
- Finally, we have additionally discussed the promising features and limitations of the proposed system.

The proposed model has been found satisfactory in terms of time taken for solutions and offers a good recall rate. Hence this model has applications for solving the complex problems with large number of inputs. This model can be utilized for multichannel sensor network where input data is very large.

1.3. Potential applications of the proposed study

- The information fusion techniques are mostly used in IoT based applications where data is generated from heterogeneous devices and integration of data is performed for the further usage of data.
- All the sensor networks use data fusion techniques to assemble to data collected from different sensors.
- The data fusion techniques are also used in military services to gather the data from multiple sources and to draw interpretations of data from security point of view.
- The data fusion techniques are also used in industry 4.0 for decision making.
- Smart cities also make use of the data fusion methods for generating useful information from the varied data.

The respite of this article is systematized subsequently: Section 2 presents the related works of information fusion applications and provides an overview of back propagation neural network (BPNN), Neural Network Analysis, information fusion principles. Section 3 states the data association techniques commonly used. Section 4 proposes a new fusion of information nanosensor multi-channel process. Section 5 shows the tests we have carried out to test the efficiency of the algorithm proposed. This analysis concludes in Section 6.

2. RELATED WORKS

Data fusion brings together information from a variety of sources with different representations of information. For both unstructured and semi-structured data forms, this approach has been used at the best. The fusion of information symbolizes, in particular, textual representations of knowledge and rich media material. We present the corresponding studies on this topic in this section.

In [10], authors have suggested a model designed to reduce diagnostics and computing complexity. They developed sensory data fusion systems with a dynamic sensor selection that integrates sensory data. In [11], information fusion method is developed for a few processes. The emphasis is given on decision-making and risk analysis [11]. In [12], authors have focused on the notion of decentralized data fusion, allowing the analysis of the impact of the noise parameter of the various sensors. The authors generalize the concept for data fusion by taking data from a single or multifunctional source into account [13]. This is suitable for various fields including remote sensing. The authors provide an overview of several concepts of data fusion that are discussed extensively [14].

The fusion of information has several advantages as seen in [15, 16]. The benefits include enhanced identification, trust and reliability, minimal data ambiguity, and an extension of spatial and temporal coverage of data. In different application contexts, data fusion may be helpful, such as wireless sensor networks, which include numerous sensor nodes, posing proficient challenges resulting from potential collisions and redundant data transmissions. Communication must be decreased to maximize the life span of the sensor nodes with energy limitations. A new fusion model is developed in [17] known as JDL. The JDL classification is based on military-related inputs and outputs. The authors describe the fusion process in the entity, circumstance, impact, and process refining that is considered to be the four increasing levels of abstraction. The limitations of JDL model are resolved by authors in extended versions [18, 19]. The idea of random sets is taken for fusion of data [20].

One of the distinctive features of this system and the generic representation scheme is the ability to integrate decision uncertainties with decisions themselves. Abstract fusion models suggested in [21] where the work is focused on which data fusion, feature fusion, decision fusion and fusion of connection information have been captured satisfactorily. Due to environmental ambiguities and inconsistencies, inexactness and inconsistencies often arise and the failure of differentiation is promoted [22]. Data fusion approaches must concentrate on surrounding redundant data to mitigate such impacts. Confluent data caused by the fusion can be difficult in particular if the scheme relies on evidence-based beliefs and the law of Dempster [23]. Conflicting data must be handled with careful attention using a data fusion algorithm to avoid counterintuitive effects. While numerous problems have been found and extensively explored, there is no data fusion algorithm capable of tackling all the above problems. The literary techniques concentrate on only a subset of these problems, which would depend entirely on implementation.

3. DATA ASSOCIATION TECHNIQUES FOR FUSION

These techniques are used to evaluate the set of measures corresponding to each nanosensor. Let's assume that X targets are monitored in a mixed environment by only one sensor. Then the issue of data association is as follows:

- From the fusion node each sensor's output is collected at distinct time intermissions;
- The sensor output is not collected at precise intermission;
- Output includes sound and observation from sensors;
- Output node specific sensor not known in every time interval.

The association of data tends to establish a collection of interpretations or measurements created over some time by the same sensor. The number of possible Sets is (P!) t-1 when an instance is a Frame-to-Frame association, and we agree that P possible points can also be found on all T frames. It should be remembered that only a single set determines the true movement of P points from all of these potential results.

The data association is completed before the state estimation of the sensors is determined. The evaluation or classification may not be correct if the data association process does not work consistently. The granularity of all fusion levels varies depending on the aim of each level and can be utilized as a data association technique. The following methods are used to address the issue of data association:

3.1. Probabilistic data association (PDA)

The PDA algorithm [25] is identified as the modified filter of all neighbors. Each hypothesis of a valid sensor measurement assigns an association probability. The results which fall on the sensor validation gate during a particular duration are a true measurement.

In all scenarios, the sensor status estimate is determined as a weighted total of the estimated state. The algorithm will combine various observations with a certain sensor. The association of the various observations with a given sensor thus allows PDA to estimate the sensor status, and the probabilities of the association are used as weights. The PDA algorithm's major drawbacks are:

(a) Path loss as the PDA does not take into account interference with other sensors, the nearest track may often be misclassified. Therefore, it performs poorly when the sensors are near or crossed;

(b) Track management as PDA assumes that the track is already defined when initialization and deletion of track have been given.

PDA is used to monitor sensors that do not modify their patterns unexpectedly.

3.2. Joint probabilistic data association

The JPDA (Joint Probabilistic Data Association) is regarded as a sub-optimal method in monitoring multiple sensors in mixed environments [26]. JPDA varies from PDA, with both sensor tests calculating the probabilities of association. JPDA takes into account and incorporates different hypotheses.

The limitations of JPDA are as follows:

(i) For the initialization of the track, an explicit technique is needed. No new track can be initialized, or tracks taken out of the measurement area by JPDA.

(ii) Applied to many sensors is a costly algorithm since there is an exponential increase in the number of hypotheses by the number of sensors.

3.3. Multiple hypothesis test

Multiple hypothesis testing (MHT) is focused on the use of more than two consecutive measures to combine outcomes with enhanced results. While other algorithms use two consecutive measurements, they are more likely to make an error. In each iteration, MHT assesses all possible hypotheses and retains new hypotheses. In a cluttered setting MHT was designed to monitor multiple sensors and to solve the multidimensional assignment problem [27]. MHT can be used to find the near optimal solution [27]. The data association problem is then combined with monitoring within a single estimation system. For estimating the MHT hypothesis, the Bayesian rule or networks are used. MHT exceeded the lower densities of false positives. It was believed. The disadvantage of MHT is the expense of evaluating and the numbers of tracks are increasing or the false positive. To solve the downside, you can take the hypothesis tree with a window. Due to its exponential time and memory, realistic implementation is also difficult. To reduce assessment costs, [27] a probabilistic MHT algorithm has been proposed in which random variables are deemed to be statistically independent and an exhaustive search listing can be avoided. This is known as the PMHT algorithm. It recognizes that previously considered to decrease the evaluation costs are the number of sensors and observations.

4. DESIGN OF INFORMATION FUSION PROCESS BASED ON MULTICHANNEL NANOSENSOR

4.1. Analysis of information fusion principle

At present, giving a comprehensive description of information fusion is challenging. Information fusion center for information from multiple sensors can be the simplest fusion can also be observed facts from several man-machine interfaces, extracting symptom information, under the action of a reasoning machine and matching these signs with the knowledge base of knowledge, to make fault diagnosis and decision making, decision level fusion [24, 25]

Sensor information fusion is described as follows according to the principle of shallow and deep:

1. Observe and collect target data with N different active or passive sensors;
2. Feature extraction of sensor output discrete or continuous time function, image data or a piece of direct attribute information, and it is defined as feature vector X_i;
3. The description of each sensor about the target is accomplished by pattern recognition of the feature vector X_i, and then grouping is performed according to the same target;
4. The data of each sensor of each target is synthesized by the fusion algorithm to obtain a consistent interpretation.

4.2. Neural network analysis

A neural network is advantageous in parallel computing, distributed storage, and fault tolerance. Therefore, adaptive learning of neural networks meets the requirements of information fusion technology processing, and its application in information fusion has been paid more and more attention [26, 27]. The neural network has been a research hotspot since it was proposed [28]. It abstractly simulates the human brain, simulates the process of human brain processing information, and establishes a simple network model. Today in the 21st century, it is still the focus of scholars' research. With the continuous research on artificial neural networks, more neural network models with different structures, functions and application types have been put forward. The newly proposed models have more perfect functions and more extensive applications [29]. The artificial neural network has been increasingly used in multi-sensor data fusion, artificial intelligence, mechanical control and other fields.

In this study, BP neural network is implemented to realize the fusion of multi-channel nanosensor information.

4.3. BP neural network

A nonlinear system that simulates the information the information processing algorithm of the cerebra is called Artificial neural network (ANN). ANN possesses powerful distributed storage of information, parallel and specialized learning. The BP description defines the BPNN model, which is built on neural network theory, as the neural network model. This is a model which has been widely used, among other aspects, in pattern recognition, intelligent control, and state forecasting. It is defined because of its simplest structure and technological maturity.

BP's neural network consists of an input layer, several hidden layers and output layer as shown in Fig. 3.

The input information of BP neural network is collected of g input learning samples P_g, and the corresponding output sample is G_g. The purpose of network learning is to update the weight continuously through the error amongst the network's definite output Q_g and the target's predictable output G_g, so that the output Q_g and gradually approach to G_g. The updated training minimizes the network's output error as far as possible so that the BP neural network can achieve the best convergence.

BP neural network transmits errors from the output layer to the input layer during learning processes by continuous pro-

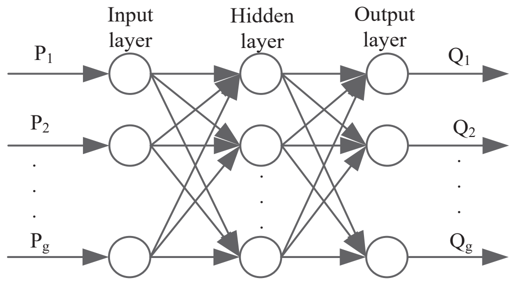

Fig. 3. BP network structure diagram

cessing of learning samples, thus continuously revising connection weights and network thresholds. Finally, the current output is very similar to the predicted output.

The BP neural network algorithm flow is represented in the following:

Step 1: initialization of the BP neural network, initial weights for individual connections, error selection;
Step 2: To use realistic problems to select input samples, and network output samples;
Step 3: Calculate, after estimation, the input of a neuron into the hidden layer and neuron output;
Step 4: Measure the computation of the error function in the output layer for the partial derivation;
Step 5: Update the connection weights for the output layer to the hidden layer;
Step 6: Update the hidden layer and input layer connection weights;
Step 7: Calculate the global mean BP neural network square error.

In equation (1), the continuous nonlinear excitement functions in BPNN must be pre-defined.

$$F\left(\mathrm{net}_{ij}\right) - 1/1 + e^{-\mathrm{net}_{ji}}, \tag{1}$$

where ji net is figured by the succeeding equations (2) and (3):

$$\mathrm{net}_{ji} = \sum_{k=N} w_{jk} \cdot PT_{ik} + \delta_k\,, \tag{2}$$

$$PT_{ik} = \left(1 + \exp\left(-\sum_{k=1}^{N} w_{jk} \cdot PT_{ik} - \delta_j\right)\right)^{-1}. \tag{3}$$

In addition, in equation (4), parameter w_{jk} can be estimated in the output layer as follows:

$$w_{jk} = \left(t_{jk} - PT_{jk}\right) PT_{jk} \left(1 - PT_{jk}\right). \tag{4}$$

Unlike the output layer, the hidden layer parameters are determined in the equation (5) as follows,

$$w_{jk} = PT_{jk} \left(1 - PT_{jk}\right) \sum_{n=1}^{n} w_{kn} u_{vj}\,. \tag{5}$$

This study designs the information fusion process of multichannel nanosensors using BP neural network. According to different fusion targets, the multi-channel nanosensor information is selected, filtered and optimized. Figure 4 depicts a specific schematic illustration of the information fusion process designed in this paper. The changes in weight are made using the steepest descent process. Depending on the location of the neuron on the network, local gradients are calculated [24]. Before training BP neural network, the multi-channel nanosensor information must be normalized to ensure that the network layer output is large enough. Here, the initial value of the center vector p_0 is determined by the training sample. The center vector, the width and the coefficient and the weight of the last layer are adjusted by the gradient descent method. During the training process, select a high learning rate first. If the training error of the latter step is greater than that of the previous step, the learning rate will be reduced, and the BP neural network will converge.

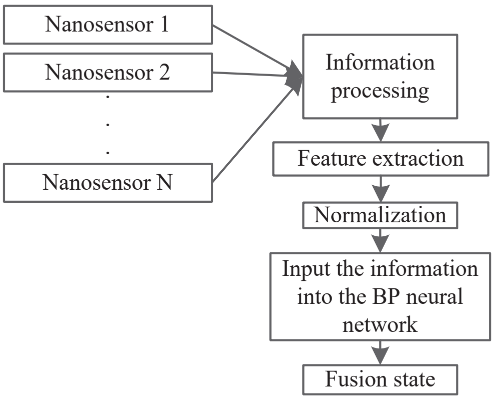

Fig. 4. BP neural network data fusion

Considering the introduction of prior information of the center vector of each category, the adjustment of network weight is limited within a certain range to avoid falling into the local minimum point.

In this paper, lossy fusion and lossless fusion of multi-channel nanosensor information fusion are considered, and the main steps are described as below:

Step 1: Use the selected nanosensors to detect the system state;

Step 2: Collect the measurement signals of the nanosensors and preprocess them;

Step 3: Select the features of the preprocessed signals of the nanosensor;

Step 4: Normalize the characteristic signals of multi-channel nanosensors to provide a standard form for the input of BP neural network;

Step 5: Normalized feature information and known system state information are taken as training samples and sent to BP neural network for training until the requirements are met. Also, the BP neural network can also reduce the measurement error. The trained network is taken as the known network. As long as the normalized multi-sensor characteristic information is sent to the network as input, the network output is the state of the system under test. Based on the above fusion process, it is assumed that the productivity of the input set is O_p, the i-th input is O_{Pi}, then the calculation formula of the fusion process controlled by BP neural network is as follows in equation (6):

$$u_p = \sum_{i=0}^{n} O_{pi} O_p \,. \tag{6}$$

By taking the above equation as an S-type function, equation (6) is transformed into the following equation (7):

$$O_{pi} = f(u_p) = \frac{1}{1+\exp(-O_p)} \,. \tag{7}$$

To reduce the error, an error function $E = \sum_p E_p$ is standardized. The calculation formula is as follows equation (8):

$$E_p = \frac{1}{2}\sum_p (d_i - O_{pi})^2 \,. \tag{8}$$

In equation (8), d_i signifies the training weight of BP neural network. A decision matrix is built after the removal of the fusion error as shown in equation (9):

$$\mathrm{H}(i,j) = \begin{cases} 1, & E_p > 0, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

In equation (9), H signifies the homologous fusion rule. When $E_p > 0$, the percentage of fusion degree is calculated by referring to different fusion error values.

Table 1 shows fusion impact matching to fusion error designed in this paper. According to the fusion effect value shown in Table 1, the larger the error value is, the worse the information fusion consequence is. To enhance the forcefulness of the multi-channel nanosensor information fusion process, the principal component analysis method is also adopted in this study to reduce the dimension of the fusion error and control the value of the fusion error. In equation (10), the fusion fault matrix is expressed:

$$\min_A \|X - A\|_F \,, \tag{10}$$

where: X is the fusion fault matrix, $A$is the low-order matrix, and $F$is the type of the matrix.

Table 1

Fusion impact matching to fusion error

No.	Error of numerical	Fusion results/%
1	0.1	72.6
2	0.2	61.3
3	0.3	55.7
4	0.4	50.4
5	0.5	46.8
6	0.6	43.7
7	0.7	40.2
8	0.8	38.6
9	0.9	32.4
10	1.0	28.5

To improve the robustness of the fusion process against sparse clamor, the matrix is putrefied into low-rank component and sparse component, and formerly the low-rank structure and sparse component are restored by solving the kernel norm optimization problem, thus forming the optimized fusion process as in equation (11):

$$\min_{A} \lambda \left\| X - \frac{\mu}{2} A \right\|_F^2 , \tag{11}$$

where: μ signifies the apprise coefficient of fusion error. Under the above optimized fusion calculation formula, the multi-channel nanosensor information fusion is finally realized.

5. EXPERIMENT

Simulation is performed to validate the applicability of the projected neural network-based method.

5.1. Experiment design

To make the experimental the experimental process clearer, the experimental scheme was specifically designed:

1. Experimental environment: The processor used in the experiment was I9-9980XE, the memory was 32 GB, the core frequency was 3.00 GHz, and the operating system was Windows 10. To guarantee the uniqueness of the experimental conditions, the number of experiments was set to 300 times.
2. Comparison method: to avoid the oneness of the experimental results, the multi-sensor data fusion method based on connected probability weighted method and based on the reliability of entropy weighting sensor measurement data conflict and fusion method for comparison and based on neural network is designed in this paper multi-channel nanometer sensor information fusion method to complete the performance verification.
3. Comparison indexes: In this study, the time spent in the fusion process and the recall rate of fusion results were selected as indexes to verify the application performance of different methods. The less time the fusion process takes, the higher the efficiency of the fusion method. The higher the recall rate of fusion results, the higher the reliability of the fusion method.

5.2. Results

5.2.1. Time-consumption for fusion of information

Firstly, the application robustness of the projected scheme and the approaches in PDA, JPDA, are compared by taking the time of fusion process as the index for comparative study. The time spent in the fusion process of different information fusion methods is presented in Table 2.

Figure 5 shows time consuming outcomes of the fusion procedure of diverse information fusion methods. When using the method PDA [25], the time of its fusion process varies between 0.65 min–0.73 min for Method JPDA [26], the time of the fusion process varies between 0.67 min–0.71 min and that for MHT [27] fusion process varies between 0.9 min–0.8 min.

Table 2
Time consuming results of the fusion process

Number of experiments/times	Time spent in fusion process/min			
	PDA [25]	JPDA [26]	MHT [27]	Proposed method
50	0.65	0.67	0.9	0.38
100	0.66	0.69	0.87	0.47
150	0.62	0.65	0.92	0.45
200	0.67	0.67	0.88	0.42
250	0.72	0.73	0.86	0.43
300	0.7	0.71	0.88	0.44

However, with the application of method in this paper, the time of fusion process varies between 0.38 min–0.44 min with the increase of the number of experiments, which is significantly less than the two traditional methods. It can be concluded that the information fusion method of multi-channel nanosensor based on a neural network designed in this paper has higher information fusion efficiency.

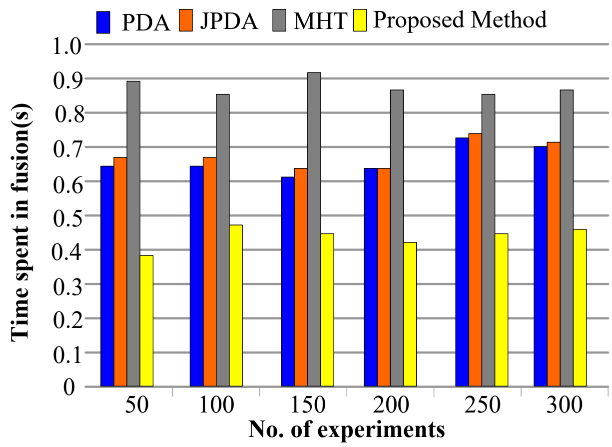

Fig. 5. Time consuming results of the information fusion processes

5.2.2. Fusion results recall rate test

To further carry out performance verification, the recall rate of fusion results was taken as the index to prove the application of the projected method, and the further three methods. The comparison and experimental outcomes are depicted Table 3 and Fig. 6.

By comparing the outcomes illustrated in Fig. 6, it observed that the recall rate of fusion results of diverse information fusion methods also changes with the number of experiments. It is clear that the recall rate of used methods PDA, JPDA and MHT varies in a very small range, but generally maintains an upward trend. It may be concluded from Fig. 6 that the recall rate of the proposed method keeps a steady rise, with a higher recall rate than the other three traditional methods.

This indicates that the proposed method has higher reliability of information fusion. In assumption, associated with the three traditional approaches, the proposed technique takes less time

Table 3
Recall rate of fusion results

Number of experiments/times	Recall rate fusion results			
	PDA [25]	JPDA [26]	MHT [27]	Proposed method
50	72.1	66.7	76.7	83.8
100	73.4	76.9	78.8	79.7
150	78.5	82.3	86.3	89.5
200	76.7	79.5	81.6	84.2
250	77.2	80.7	78.8	82.4
300	81.9	83.7	83.9	85.7

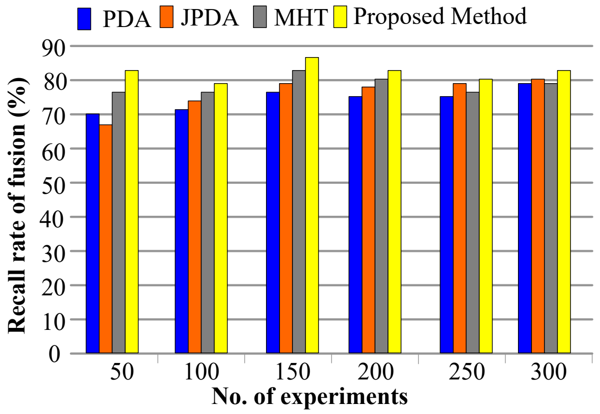

Fig. 6. Recall rate of fusion results of diverse information fusion methods

in the fusion process and has a higher recall rate of fusion results, indicating higher efficiency and reliability.

5.3. Analysis

The integration of data is very important these days as the data is collected through different sensors and the interpretation of data is only possible after integration of data. The proposed method is based on the potential of neural networks which are able to learn from the environment dynamically where the data is available in high volume and can be fused by using BP neural networks to generate important information for drawing further inferences from the raw data. The results of the fused data are evaluated on the basis of two performance metrics, time taken for fusion of data and recall score of the algorithm. It is proved that the proposed method takes minimal time as compared to the conventional works in generating fused data from the data collected from diverse sites or sources. This method can be utilized for fusion of data collected from IoT based sensors, in smart cities where information is collected from smart devices and then processed, in Industry 4.0 where everything is connected through smart and sensor-based devices. The proposed method can be used for fusion of data and in future we can extend the work by adding analytical component to draw inferences from the fused data for generating reports and for obtaining productive information.

6. CONCLUSIONS

To solve the problems of the time-consuming fusion process and poor recall rate achieved by the traditional methods, this study designs a neural network-based multi-channel nanosensor information fusion method. The proposed method analyzes the theory of neural networks and adopts the BP neural network as the tool for fusing the information gathered from different sources. The proposed multi-channel nanosensor information fusion method is designed to get trained from the gathered information which deals with the normalization processing, training, and output process. In addition to it, experiments are designed in this study to evaluate the time taken by the algorithms to generate the fused data and to evaluate the recall score achieved by the algorithms for fusing the data. It is found that the for different iterations start from 50, 100, 150, 200, 250 and end with 300, the proposed method processes the information in a minimal span of time whereas the conventional methods such as PDA, MHT and JDPA take more time in processing the data. Secondly the recall score attained by the proposed method is the best among all the methods taken for comparative study. In future, one more component will be added to interpret the data for generating desired reports after fusion of data.

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