SSOMs Applied with Bayesian Inference Considering Plasticity and Stability Factors Depending on Data Characteristics

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Abstract. In the present study, the SSOM applied with Bayesian inference was designed so that its plasticity which is the degree of reflecting input data and its stability which is the degree of stable remembering would harmonize with each other by obtaining the probability for data to belong to groups based on their characteristics to apply their importance and error rates to learning rates and neighboring radii. The SSOM applied with Bayesian inference learns data collected from gas piping through diverse sensors having different bases to classify risk conditions. The results of classification of data into those with high error rates and those with low error rates were compared with those of existing SSOMs and the results of the comparison showed that, in the case of data with high error rates, cases where they were learned considering their characteristics had higher accuracy

Keywords: SOM, Bayesian interface, Competitive learning, Plasticity, Stability

1 Introduction

Learning data include those of high importance and those with high error rates. During learning, these data should be learned applying learning coefficients depending on data considering data characteristics. To complement this condition, the purpose of the present study is to design an SSOM learning algorithm that applies the characteristics, importance and error rates on learning data through Bayesian inference. The SSOM applied with Bayesian inference is designed so that its plasticity which is the degree of reflecting input data and its stability which is the degree of stable remembering would harmonize with each other by obtaining the probability for data to belong to groups based on their characteristics to apply their importance and error rates to learning rates and neighboring radii.

The Self-Organizing Maps proposed by Kohonen is a sort of neural networks which is a unsupervised learning algorithm [1, 2]. The SSOM (Spherical Self-Organizing Maps) is a learning algorithm made by applying the SOM learning algorithm as such to maps in old forms to complement the border effect occurring during SOM learning in existing 2-D maps [3]. In the case of clustering algorithms such as the SSOM, if an input data once belongs to a certain cluster, the input data should stably belong to the cluster until the leaning is completed. When data have been entered, the data should be actively reflected on the learning map to proceed with learning. However, the SSOM basically learns data using competitive learning. Competitive learning refers to a system where many output nodes compete when a data has been entered so that the most similar node to the input data becomes the winner and the data is learned centering in the node. Although competitive learning actively reflect new input data on learning results, its stability which is the degree of stable remembering is low[4]. However, if stability is unilaterally enhanced, it will face a dilemma of reduced plasticity on the contrary.

Bayesian theory is a method where prior probabilities are given to all hypotheses, new hypotheses are inferred when current measured values have been given and then the prior probabilities are renewed with ex post facto probabilities depending on facts related with the hypotheses to infer probabilities[5, 6]. Therefore, the probabilities for input data to belong to clusters are obtained using Bayesian inference and using the probabilities, the importance and error rates of the input data are calculated and applied to learning rates and the sizes of neighboring radii during SSOM learning. The designed SSOM applied with Bayesian learns data collected from gas piping through diverse sensors having different bases to classify risk states.

2 Background

The SOM is a sort of neural networks used in the area of machine learning which is a learning algorithm made by Kohonen by modeling the structural changes in neurons and synapses occurring in the process of human’s learning. The SOM consists of an input layer which is a layer of input data, an output layer which is a layer of storage data stored in the SOM map and 2-D grid structures completely connected from the input layer to the output layer in two layers. SOM learning occurs in the competitive learning method which is a winner-take-all system where only the winner node (Best Matching Unit) which is a data the most similar to the input data in the output data layer and other nodes that are within the neighboring radius centered on the winner node can learn. The SSOM was made by applying the SOM learning to old maps so that the same neighboring radius can be applied no matter which node in the output layer is selected as a winner node to complement.

Based on the Bayesian theory, Bayesian inference infers probabilities by renewing prior probabilities with ex post facto probabilities when new facts have been identified based on evidence depending on the degree of belief thus far. Prior probabilities are renewed with ex post facto probabilities using LS and LN which are the degree of belief in data entered by experts. Since LS and LN values are the degrees of belief in data, larger LS values mean that the degree of belief in data is higher when values within the range presented by experts belong to the data. On the other hand, smaller LN values mean that the degree of belief in data is lower when values within the range presented by experts do not belong to the data.

The SSOM learns using competitive learning where output nodes in the output layer compete in order to be selected as the winner node. Competitive learning has good plasticity but low stability. Plasticity refers to the degree to which input data are reflected on learning results. Stability refers to the probability for an input data that has once become to belong to a certain cluster to continuously belong to the cluster. In the present study, Bayesian inference is applied to SSOM learning to design a learning algorithm to complement the dilemma of plasticity and stability.

3 SSOM applied with Bayesian

The SSOM applied with Bayesian obtains the probabilities for input data to belong to clusters to apply importance and error rates to learning rates and neighboring radii in order to achieve harmony between stability and plasticity.

In the present study, to complement such a dilemma of stability and plasticity, an SSOM learning method to consider the importance and error rates of data through Bayesian is designed. Learning data have different degrees of importance and error rates depending on the purpose of learning and situations. Those degrees of importance and error rates are obtained through Bayesian to apply the learning rates and neighboring radii of SSOM learning in accordance with data. Existing SSOMs conducted learning with a certain learning rate and neighboring radius regardless of the importance and error rates of learning data. However, since individual input data have different degrees of effects on the purpose and results of learning, data should be applied to the learning map differently based on the importance and error rates of the data. In the present study, such degrees of importance are applied by obtaining the importance and error rates of the data through Bayesian reflecting experts' opinions.

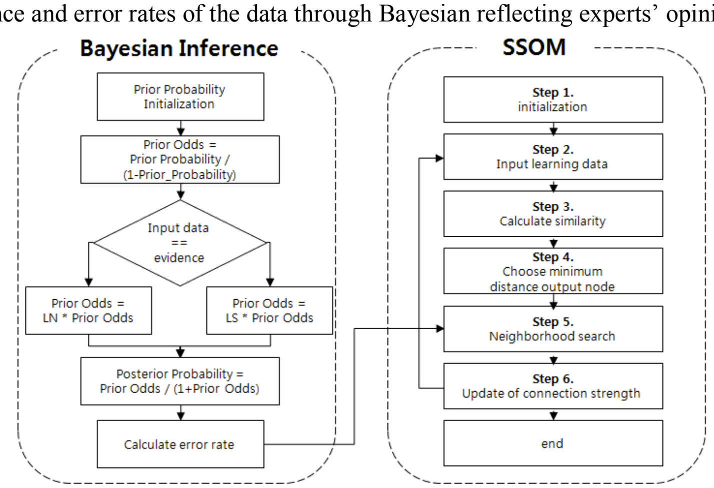

Fig. 1. SSOM applied with Bayesian inference

For instance, consider that there is a system to classify normal data from sensor data having a range of normal states and a range of dangerous states along the vertical line. The range of normal states has values in a range of 0~50 and the range of dangerous states has values in a range of 51~100. Data with high prediction rates in classifying normal states are values close to 25. These data are inferred as having high probabilities to be normal through Bayesian and thus are identified as data of high importance; they should be learned at enhanced learning rates. Values in a range of 45~55 are normal data but actually in dangerous states and thus they are quite likely to be data with high error rates. Therefore, instead of enhancing learning rates to raise plasticity, the neighboring radius should be increased to enhance stability by having many output nodes learn the data.

The Bayesian inference calculates the error rates of the values, and obtains the importance. Fig. 1 shows our SSOM learning algorithm with Bayesian which considers their stability and plasticity per data. The SSOM's learning processes consist of a total of six steps. The importance and error rates of data are obtained through Bayesian when data have been entered at step 2 and are applied to the neighboring radius at step 5 to select output nodes to learn the data and adjust the strength of connection for learning. Bayesian inference receives LS and LN which are the degrees of belief in data that satisfy the purpose of learning before learning to apply them to Bayesian inference. Through this, the importance of data which is the probability for the data to satisfy the purpose of learning is obtained when data have been entered at step 2 of SSOM learning. As shown in Figure n, Bayesian inference initializes prior probabilities into 0.5 to obtain ex post facto possibilities and then, uses the ex post facto possibilities to obtain ex post facto probabilities. The obtained ex post facto probability values are applied to learning rates during SSOM learning and are renewed with prior probabilities for the next input data to continuously obtain the importance and learning rates of input data.

The probability values and importance of data inferred by Bayesian Inference are compared to actual states to obtain error rates in order to calculate the neighboring radius. The calculated size of the neighboring radius is applied to step 5 of SSOM learning to search for neighboring nodes. The strength of connection of the neighboring nodes including the winner node is adjusted by the learning rates obtained through Bayesian Inference before the nodes learn the data. The SSOM designed considering the importance and error rates of data through Bayesian as such applies residuals which are differences in similarity between the BMU selected when data have been entered and input data to systems that judge dangerous situations to analyze in comparison with existing SSOMs.

4 Experiment

The SSOM applied with Bayesian proposed in the present study can learn data collected through multiple sensors with diverse bases to judge current states. Using the proposed system, dangerous states were classified based on sensor data collected from gas piping and the results were compared and analyzed with the results of dangerous state classification by existing SSOMs. Data actually collected from normal states were learned to classify dangerous states using residuals [7].

In the proposed system, when sensor data have been entered, learning and classification are conducted simultaneously through a total of four steps. The sensor data collected at step 1 are normalized into SOM characteristic vectors at step2 for SSOM learning. The SOM characteristic vectors normalized as such are used as input data at step 3. To classify dangerous states, the similarity between the input data and BMU is judged using Euclid distances at step 4. As for judgment of dangerous states, if the value of the similarity between the input data and BMU exceeds the threshold, the state will be judged as being dangerous and classified.

The system designed as such is applied with data from protection potential sensors, protection current sensors, gas leak sensors and flooding sensors installed in gas piping. Before learning the data collected through these sensors, the data are normalized into SOM characteristic vectors for nodes in the input layer and the output layer. Data within the individual normal ranges are normalized in values in a range of 0~1 and four of the sensor data are normalized into a 4-D vector. Before learning the values normalized as such, to obtain the degrees of importance by data for input nodes, LS and LN values which are the values of belief in the data are received from experts by data range. In the present study, the LS and LN values by range applied to Bayesian inference were 0.8 and 0.2 respectively for the range 0~0.2, 1 and 0.1 respectively for the range 0.21~ 0.3, 0.6 and 0.3 respectively for the range 0.31~0.5 and 0.1 and 0.9 for the range 0.51~1.

If the normal state probability value of a data obtained by an input node through Bayesian does not exceed the threshold value, the data indicates a high probability of dangerous conditions when judged by experts. However, since the learning data were collected from actually normal sates, the data are classified into those with high error rates and thus are learned with an increased neighboring radius. On the contrary, if the data indicates a high probability value of normal conditions, the actual conditions were judged identically to the value judged by experts. Therefore, the data will be classified into those with low error rates and learned with a reduced neighboring radius.

The results of judgment of dangerous states through the present system and the results of judgment of dangerous states using an existing SOM. The present system and the existing SOM used a total of 2000 data on normal states as learning data. In a learning map configured as such, the data were classified into a total of 200 data consisting of 100 each of those with high error rates and those with low error rates corresponding to normal states and dangerous states respectively. Then, the most similar BMUs to input nodes were searched for among these data in the learning map and their similarity to input nodes were obtained using Euclid distances. Thereafter, those data with a similarity value under the threshold value were classified into those indicating normal states. The results of classification of data with low error rates and the results of learning and classification of data with high error rates. Among 200 data with low error rates that should be actually judged as indicating normal states, 200 were correctly classified by the existing SOM and 200 were correctly classified by the present system respectively. Among 200 data with high error rates that should be actually judged as indicating normal states, 77 were correctly classified by the existing SOM and 200 were correctly classified by the present respectively.

As such, the experimental results show that accuracy was different between the results of learning considering data characteristics using the present system and the results of learning without considering the importance and error rates of data. Although data with low error rates did not show clear differences between cases where data characteristics were considered and cases where data characteristics were not considered, it can be seen that in the case of data with high error rates, the accuracy was much higher when data characteristics were considered. As such, the experimental results indicate that during learning, the importance and error rates of data as data characteristics should be considered.

5 Conclusion

The present paper proposed an SSOM learning algorithm applied with Bayesian inference in order to achieve harmony between stability and plasticity which are in competing relationships in competitive learning. Unlike existing SSOM algorithms, the proposed algorithm was designed so that data of high importance with high accuracy and prediction rates that satisfy the purpose of learning can be obtained through Bayesian inference to adjust learning rates and data with high error rates classified differently from actual states can be learned after adjusting the neighboring radius.

The SSOM applied with Bayesian inference has a structure suitable for classifying data with high error rates when diverse data are classified. Depending on data, the SSOM applied with Bayesian inference can also improve the accuracy of classification of data of clear importance or data having ambiguous bases for classification.

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