Graphical Analysis of Time-series Data from Waste Incinerator Using Self-organizing map

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Abstract

The emission of dioxins from waste incinerators is one of the most important environmental problems today. It is known that optimization of waste incinerator controllers is a very difficult problem due to the complex nature of the dynamic environment within the incinerator.

In this paper, we propose applying self-organizing map (SOM) for visualizing topological information of waste incinerator data for time-series data, and aimed at finding correlation in real waste incinerator data to predict high dioxin emission.

1. Introduction

The emission of dioxins from waste incinerators is one of the most important environmental problems today. It is known that optimization of waste incinerator controllers is a very difficult problem due to the complex nature of the dynamic environment within the incinerator. This is because the environment in the incinerator is a complex dynamic environment in which the different items are dependent on each other, and is not a simple dependency relationship.

There has been past research in intelligent estimation of dioxins emission from waste incinerators. Fujiyoshi et al [1] has proposed applying fuzzy control to incinerator control to decrease the dioxins emission. Ichihashi et. al [2] has applied statistical analysis to calculate the correlation of various input signals with dioxins emissions. Fukushima [3] has proposed applying fractal fuzzy control in order to estimate and control dioxins emission.

For this research we investigate methods applying SOM to classify time-series data for complex environments, and propose applying self-organizing map (SOM) for visualizing topological information of waste incinerator data for time-series data. Our aim is to find correlation in real waste incinerator data to predict high dioxin emission.

2. Training Requirements for Waste Incinerators

For this experiment, we used sensor data from a waste incinerator plant as the time-series data, and aimed at visually classifying instances of high dioxin emission. We used real waste incinerator data provided by Hitachi Zosen Corporation. Figure 1 shows the schematic diagram of the fluidized bed waste incinerator.

The data consists of the following 12 sensor values measuring various conditions of the incinerator. Flapper angle (0 - 100.00%), oxygen concentration in incinerator exit (0 - 25.000%), garbage rate (t/H), incinerator temperature (0 - 1200.0 ℃), carbon monoxide concentration (0 - 500.0ppm), incinerator pressure (-2000.0 - 1000.0ppm), cooling liquid rate (0-1.0000m3/h), conveyer belt speed (0 - 7.000rpm), primary air supply(0 - 7.500KNm3/h), secondary air supply base (0 - 7.500Nm3/h), secondary air supply modification (0 - 7.500KNm3/h).

It is known that CO (carbon monoxide) concentration over 100ppm show strong correlation with dioxins

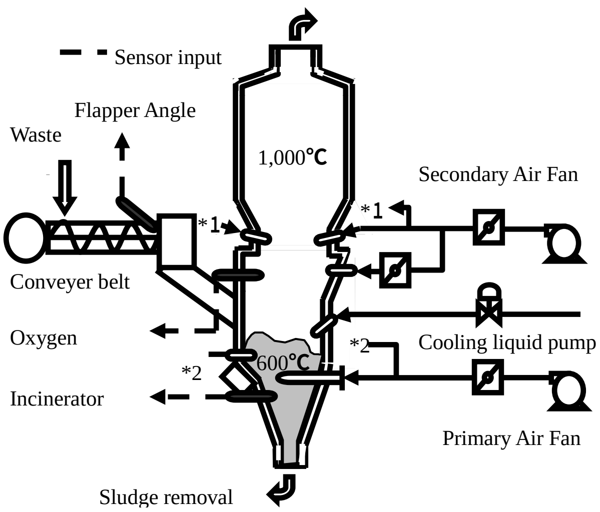

Figure 1. Schematic diagram of Fluidized Bed

concentration. For this research, we use the CO concentration as the target output, and aim to reduce the average CO concentration as well as to reduce the number of CO concentration peaks over 100ppm.

3. Learning Time-series Data using Self-organizing map

Self-organizing map (SOM) is a type of artificial neural networks proposed by Kohonen[5]. It is trained using unsupervised learning to produce low dimensional representation of the training samples while preserving the topological information of the input space. SOM applies neighborhood learning to enable the creation of close output for similar input. This feature is effective for classification and visualizing in complex problems.

On the other hand, standard SOM cannot directly handle time-series data. Several approaches to allow SOM to learn patterns in time-series data have been previously proposed, such as adding a feedback loop[7] to create a multi-layer SOM, and adding delayed time units to SOM[6].

For this research, we used delayed-time units in order to map time-series data into the input pattern space. Figure 2 shows the model of time-series data that consists of two elements (A, B) is input to SOM using delayed-time unit. Its approach to learn patterns in time-series data does not require change in the SOM method, because it is possible to implement the additional input by preprocessing.

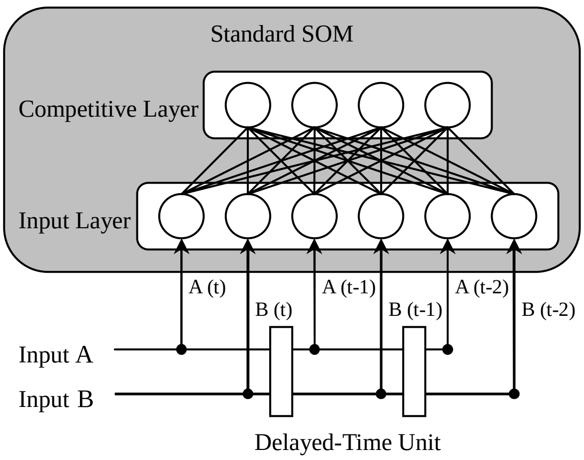

Figure 2. Model of SOM using Delayed-Time Unit

4. Method for Visualizing Information of Time-series Data

For this research we use delayed-time units to learn time-series pattern on SOM. For the output we construct the map using the weight values of the competitive layer.

For this experiment we construct the following two patterns of maps. The first pattern of maps is visualized from difference between predicted values and the actual values of each sensor recorded for the same time frame. For the values of predicted sensor values, the weight values of winner node at each time frame were used. In this map, the purpose is to display the state of the sensor value in each time frame.

The second pattern of maps is visualized from weight values of each element of the time-series data. For example, using time-series data that consists of three elements (A, B, C), three maps are constructed for each elements. These maps can be displayed by using AND operation (ex. [A AND B,] [A AND B], and [B AND C]). This function has the aim of displaying correlation from each element of data.

Additionally, for this experiment we draw the tracks of the winner node for each time frame over the above two maps. Figure 3 shows the method for drawing tracks of the winner node. Tracks of winner nodes are drawn in a line such that newer data are emphasized. Drawing tracks of winner node have the aim of presenting the change in the temporal pattern in the visually.

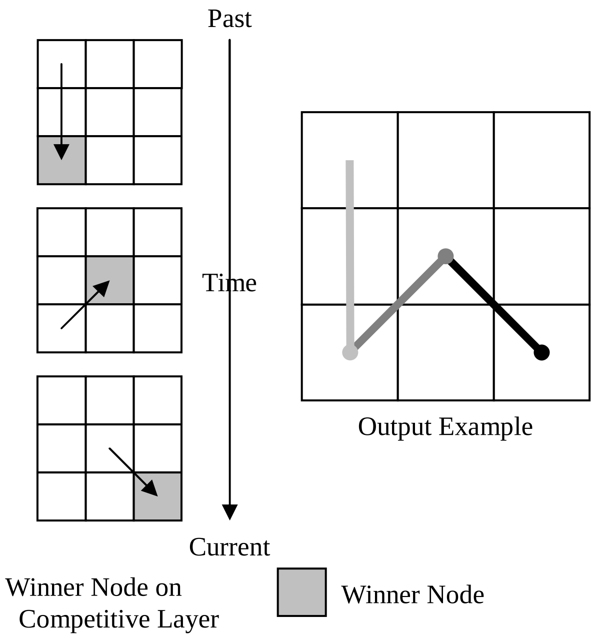

Figure 3. Visualizing Tracks of Winner Node

5. Experiment Result

For the SOM input data, we use all of the 12 sensor types, and 20 continuous time-series data (each data at 30 seconds delay for 10 minutes) per each sensor type as 1 time-series sequence. The input data used for learning was selected from a day high frequency of abnormal range of CO (>100ppm) from the incinerator sensor data base. 15000 time-series sequences were used for the input data set.

For this experiment we used following SOM. The competitive layer of size the 100x100, and the weights for the competitive layer was initialized by random. For neighborhood function we use the Gaussian type. For the decision of winner node we use Euclidian distance.

Figure 4 and Figure 5 is the maps that constricted by proposed method at the same time frame. Figure 6 shows the change of the time series of CO concentration corresponding to tracks of the winner node. Figure 4 shows that the map that consists of difference between predicted values and the actual values was able to visually represent low and high dioxin emission combustion states. Similarly, Figure 5 shows that the map that consists of an element of sensor data was able to visually classify abnormal range.

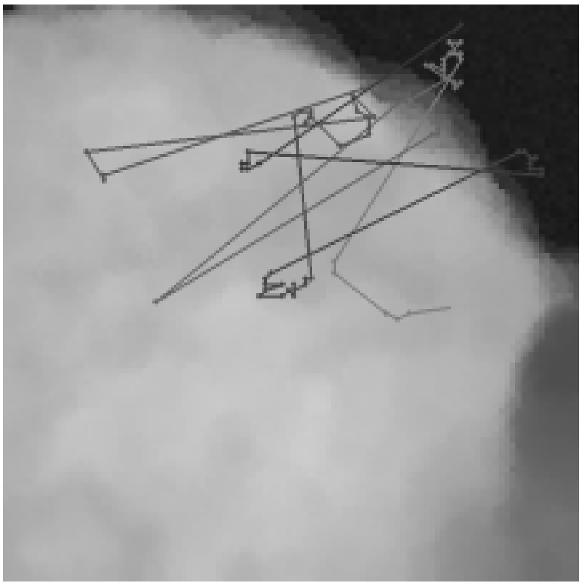

Figure 4. Map of difference between predicted values and the actual values

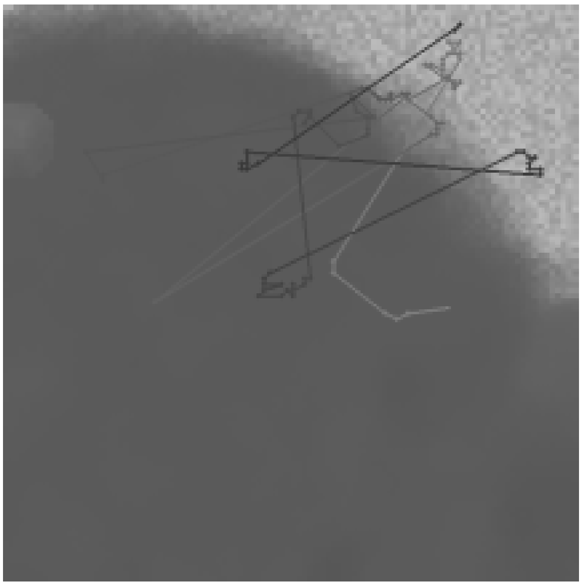

Figure 5. Map of an Elements Weight Values (CO concentration)

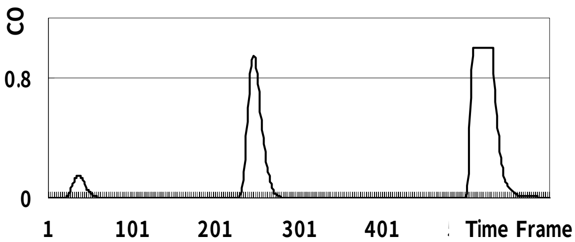

Figure 6. CO Concentration

6. Conclusion

Through computer simulation, we showed that the proposed SOM method was able to visually represent low and high dioxin emission combustion states. The change in state of the waste incinerator was able to be confirmed by drawing tracks of the winner node visually. Further, we felt that the tracks of the winner node contain important information on the time-series pattern.

For future works, we will consider methods to visualize time-series patterns, as well as reevaluate learning method for time-series data using SOM. Specially, we plan to divide the learning of time-series data in two stages. We hope that by separately training the time-series pattern and state at a time frame will enable visualizing these information more directly.

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