# Recoverable Lost Node to Overcome a Problem of the Single Winner Node by ASOM

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**Summary**

The Self-Organizing Map (SOM) is a neural network algorithm based on unsupervised learning. The weight initialization is very important for training data. Because the appropriate weight initializations enable a learning convergence to global or local minima to be more correctly. However, traditional weight initialization is randomized in a range of 0 and 1. This results in a problem of a single winner node, which leads to miss of clustering because the initial value is not related to the input datasets. Additionally, the learning convergence is very slow when the initialize value is long distance from the dataset. This paper presents a novel method called as Ant Self Organize Map (ASOM) to alleviate such problems. A proposed original idea is that lost node is recoverable to overcome the problem of a single winner node by exchanging from new datasets. The proposed ASOM is based on the Ant Colony Optimization (ACO) and Fuzzy Ants Clustering as following. Firstly, weight initialization is done from random input data which is selected by a probability of loading. This technique of selecting is applied from Fuzzy Ant Clustering. Secondly, exchange connection weights for lose nodes are made by the methodology of Pheromone of Ant which will keep records of winner and lost nodes. Lost nodes which have pheromone values less than a given threshold are re-initialized by randomizing from new datasets. From the experimental result, it is found that the average of accuracy rates increases up to nearly 16 % when compared with traditional SOM on standard datasets e.g. iris datasets.

***Key words:***

*The Self-Organizing Map, Data Clustering*

## 1. Introduction

Data Clustering is one of the most important unsupervised learning techniques. Kohonen's Self-Organize Map is known as a good technique for clustering large-scale databases [1,2,3,4,5,6,7,8,9,10,11].

Even though Self-Organizing Map (SOM) or conventional clustering methods have their superior features for clustering analysis, their combinations into two-stage methods are generally much more powerful than individual methods such as the ant-based SOM clustering model [12].

The SOM is an unsupervised learning technique which consists of 2 steps for learning. In first step, weight initializations are randomized in a range of 0 to 1. This method is typically used for normalized data. However, these data will be lost scaling information. Additionally, a problem of a single winner node is appeared when the number of member in each class is more different. This is resulting in missing clustering. Tsutomu Miyoshi [13] proposed an idea of using input data space as initialized nodes connection weights known as initial node exchange. This method gives a better performance in time reduced to complete learning and the average of moving distance of all nodes when compared with traditional randomized in a range of 0 to 1. This is because the connection weights are initialed directly from input space without input from outside. This method can solve the problem of the attribute with multi-scale but it cannot overcome the problem of the difference in the number of dataset. Because a random value from selected dataset used to be the initial value for each connection weight may come from the same class of dataset. For example, the glass datasets (well-known dataset) contains of two classes. A number of first class is 163 while a number of member second class is only 51. From experiments in [13] show that if the glass dataset is used, there is only a single winner node and this result in a wrong of classification. In second step, the finding winner node and the weight update are performed.

Thus, in this paper proposed a novel methodology to improve the accuracy in classification. In order to alleviate the problem of the single winner node which is caused from the difference in the number of dataset, this paper presents a novel idea for selecting appropriate initial value called as ASOM. The proposed ASOM consists of two states. One is an initial state, and the other is an exchange state. In the initial state, initialized value is randomized from input datasets in order to overcome the single winner node problem. Then, in the exchange state, a new class is used as an indicator to make decision whether the initialized value is good or not. If not, the initial value is changed by random from dataset.

Initial nodes are exchanged by using initialized values of connection weights which is input node. This method is handled without the input from the outside. Therefore, the initialization process and initial node exchange process

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can be completed without specific learning data, which selected by probability of loading $P_{load}$ from Fuzzy Ant clustering [14, 15, 16, 17, 18, 19, 20, 21, 22, 23]. The weight initialization from random data by a probability of loading will make good weights which come from datasets. Additionally, the probability of loading avoids the local minimum problem. Finally, the good weight initializations will be obtained by the proposed algorithm in the initial state.

The traditional training or learning is more powerful by the additional proposed exchange state. Although good initial weights will be obtained by the proposed method in the initial state, the training with a large of data makes a problem of the local minimum. To solve this problem, this paper also presents a novel process of evaluation which is the additional from traditional training in the proposed exchange state. The evaluation process is applied from ant optimization. Pheromone of ant will be increased for a node which is the winner node in each epoch.

A lost node which its pheromone density is less than $T_{create}$ will be exchanged by a new initial value from input space by using $P_{load}$. The local minimum problem is avoided by the proposed method. In conclusion, the proposed algorithm is an integration of Ant colony Optimization and Fuzzy Ant Clustering in the Self-Organize Map. This introduces a fast learning convergence and more accuracy in clustering.

The rest of this paper is organized as follows: In section 2, authors state background of the Self-Organize Map. In section 3, authors propose Ant Self-Organize Map (ASOM). In section 4, experiment and result are presented. In section 5, discussion is stated and Section 6 offers conclusions.

## 2. Background of the Self-Organize Map (SOM)

Kohonen's Self Organizing Maps (SOM) [1], a neural network algorithm based on unsupervised learning and competitive neighborhood learning. Prototype of SOM consisted of 2 layers: Input layer and Output Layer. The output layer represents data of each group. In learning process, the output layer nodes compete with each other in order to get the winner node. The connection weight which is the closest to the input data in terms of Euclidean distance is selected as the winner node which will be the output layer [13]. Connection weight of the winner node and its neighbor nodes are then adjusted by trying to close the direction of the input pattern. However, traditional weight initialization is randomized in a range of 0 and 1. This results in a problem of a single winner node, which leads to miss of clustering because the initial value is not related to the input datasets. Additionally, the learning convergence is very slow when the initialize value is long distance from the dataset.

Therefore, winner node would be initialized, but cannot initial others node.

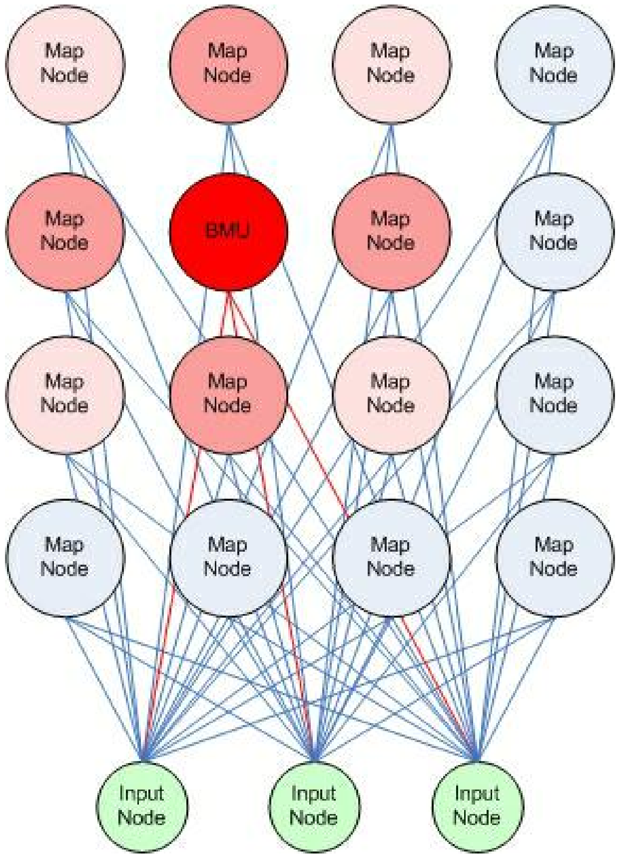


Fig. 1 Concept of Self-Organize Map

### 2.1 Initialization Stage and Parameter setting

Initial weight vectors with small arbitrary values

$$W = \{W_1, W_2, W_3, \ldots W_k\}$$

### 2.2 Training Process

Step 1: Find winner nodes or the Best Match Unit (BMU)

$$BMU = \arg\min_i \{\|Data_t - W_i\|\}. \quad (1)$$

Step 2: Update the weight vector of the winning node and the neighbor nodes

$$W_i(t+1) = W_i(t) + \alpha(t) h_{ci}(t)\left[Data - W_i(t)\right] \qquad (2)$$

Where

$\alpha(t)$ is the learning rate for iteration t

$W_i(t)$ is the weight vector of the winning node

$h_{ci}(t) = \exp(-\frac{\|r_c - r_i\|^2}{2\delta^2(t)})$ is the neighborhood function

$r_c, r_i \in \Re$ are the radius of BMU

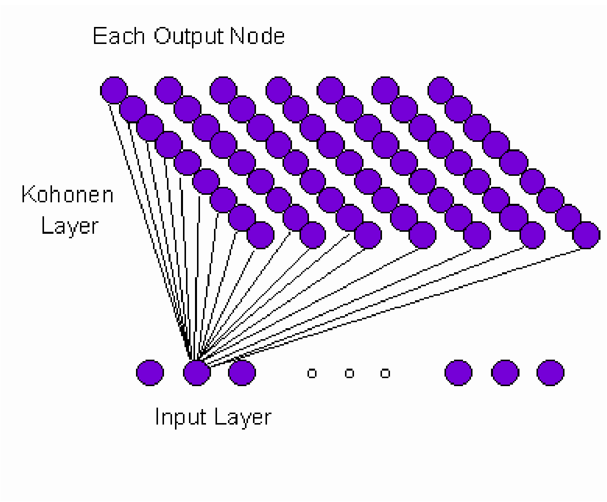


Fig. 2 Problem of Self-Organizing Map present only winner node to connecting

## 3. Ant Self-Organizing Map (ASOM)

### 3.1 Conceptual

The proposed model can be divided into five steps as shown in figure 3. Step 1 is to initialize weights which is selected from input node. Additionally, Ant picking up a single object method is proposed to be criteria for making decision. $P_{load}$ is given as 0.6 according to [14] . Step 2 is SOM training and resulting in getting winner node. Then, weight update of winner node is performed. Step 3 is to accumulate pheromone of winner node. This step presents to keep record for each node. Step 4 is to examine the record for each node and then lost nodes which are node with low pheromone density are found. Step 5 is to exchange node. A value of the lost node is changed by ant approach. Re-initialized weight for the lost node is taken place. It should be noted that re-initial will be chosen from input node without duplicate node.

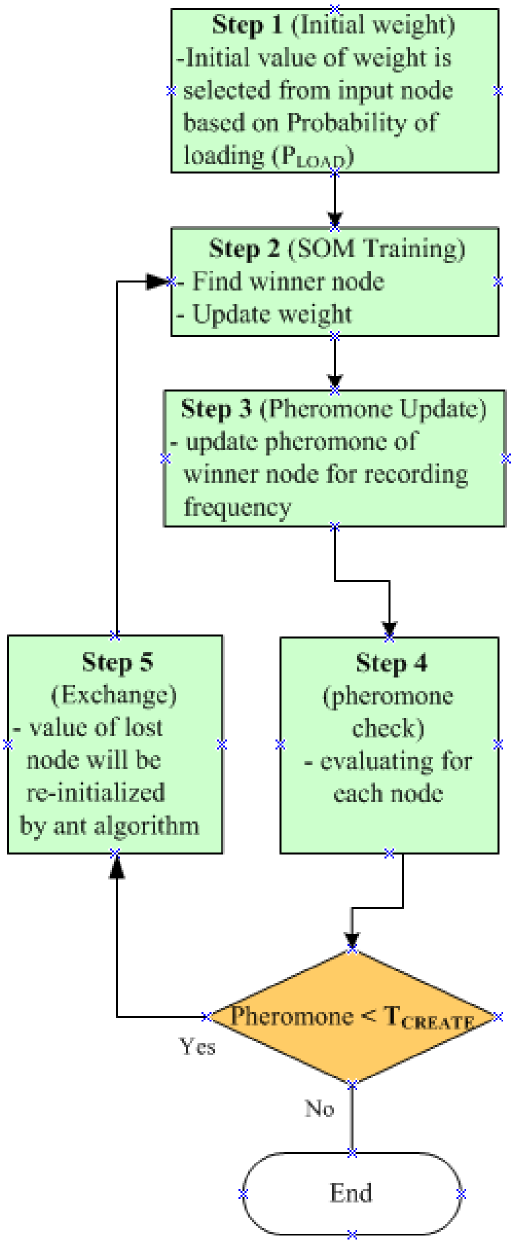


Fig. 3 Conceptual of Ant Self-Organizing Map

## 3.2 Diagram

The proposed algorithm which is used for clustering consists of three states as shown in a figure 3. The novel idea in this paper is both state 1 and state 3 which are to apply ant algorithm picking up value of input node into initial weight. In other words, the proposed algorithm is a feed-back control as shown in a figure 4. After training state, if winner and lost node is all node, this means that lost node will be feed back to the exchange state for re-initial. And then, training state is re-processed with all nodes which include both obtained winner node and initial value of lost node. Otherwise, the process will get only winner node without lost node, this means that weight of all node are stable and stop.

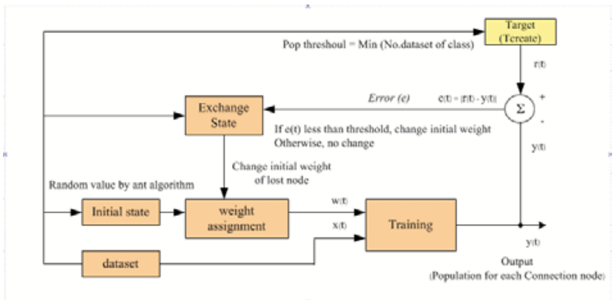


Fig. 4 Diagram of Ant Self-Organizing Map

## 3.3 The proposed algorithm

In this study, we proposed ASOM, in order to avoid falling into local minimum during the solution search process. The algorithm detail is presented below.

### 3.3.1 Initialization Stage and Parameter setting

A: Define number of clustering equal to number of weight ($N_w$)

B: Define number of feature ($N_f$)

C: Define number of sample of data ($N_d$)

D: Initial weight vector $W$ by selected randomly from dataset number equal to $k$

$$W = \{W_1, W_2, W_3, \ldots W_k\}$$

### 3.3.2 Training Process

Step 1: Find winner nodes or the Best Match Unit (BMU)

$$BMU = \arg\min_i \{\|Data_t - W_i\|\}. \tag{1}$$

Step 2: Update the weight vector of the winning node and the neighbor nodes

$$W_i(t+1) = W_i(t) + \alpha(t) h_{ci}(t)[Data - W_i(t)] \tag{2}$$

Where

$\alpha(t)$ is the learning rate for iteration t

$W_i(t)$ is the weight vector of the winning node

Step 3: Update the accumulate value for winner nodes (BMU)

$$A_i = A_i + \frac{1}{N_d} \tag{4}$$

Step 4: Check accumulate value for change lost node by selected randomly from dataset

$$W_i = \begin{Bmatrix} Data_{random}, A_i < T_{create} \\ W_i, A_i \geq T_{create} \end{Bmatrix} \tag{5}$$

Step 5: The stopping criteria by checking different of changing of weight vector $W$

**Algorithm 1** ASOM Algorithm

**Require:** $\{\mathbf{Data}_{N_f}\}_{k=1}^{N_d}$, $N_w$, $N_f$, $N_d$

Not necessary to normalize feature value between 0 and 1

**Ensure:** $\mathbf{W}_i$

**for** $epoch \leftarrow 1$ to number of epoch **do**
  **for** $j \leftarrow 1$ to $N_w$ **do**
    $\mathbf{W}_j \leftarrow Data_{random}$
  **end for**
  **for** $k \leftarrow 1$ to $N_d$ **do**
    $A_j \leftarrow 0$ ; $j = 1..N_w$
    $i \leftarrow \arg\min \|W - Data_k\|$
    $W_i(t+1) \leftarrow W_i(t) + \alpha(t)h(t)[Data_k - W_i(t)]$
    $A_i \leftarrow A_i + \frac{1}{N_d}$
  **end for**
  **for** $j \leftarrow 1$ to $N_w$ **do**
    **if** $A_j < T_{create}$ **then**
      $W_j \leftarrow Data_{random}$
    **end if**
  **end for**
**end for**

## 4. Experimental and Result

The proposed algorithm was tested with three standards dataset: Iris Plant database, Wine Recognition database and Glass Identification database.

### 4.1 Iris Dataset

This data set contains information about different types of Iris flowers. The data set consists of 150 examples each with four numeric predictive attributes. The data set contains 3 classes of 50 examples each, where each class refers to a type of Iris plant. One class is linearly separable from the other 2; the others have some overlap.

### 4.2 Wine Dataset

The data is the result of a chemical analysis of wines grown in a region in Italy but derived from three different cultivars. The dataset consists of 178 examples each with 13 continuous attributes. The data set contains 3 classes with the following class distribution class 1 have 59 examples class 2 have 71 examples class 3 have 48 examples.

### 4.3 Glass dataset

The data set consists of 214 examples each with 9 continuous attributes. The data set contains 2 classes with the following class distribution class 1 have 163 examples and class 2 have 51 examples.

Table 1: Parameter Value

| ***Dataset*** | $P_{load}$ | $T_{create}$ | ***Nm*** |
|---|---|---|---|
| Iris | 0.6 | 0.25 | 3 |
| Wine | 0.6 | 0.2 | 3 |
| Glass | 0.6 | 0.2 | 2 |

### 4.4 Result

The reported results were averaged for 200 runs of the experiments, which have a number of epochs or numbers of ant were between 20 and 4000. In each run, define for $P_{load}$ , $T_{create}$ and $N_w$ which were listed separately for each experiment. The results for the three sets of parameters for the datasets are shown in Table 1.

Table 2: Error comparison between Fuzzy Any, Initial SOM and ASOM.

| ***Dataset*** | ***N class*** | ***N feature*** | ***Err. Fuzzy Ant*** | ***Err. Int. Som*** | ***Err ASOM*** |
|---|---|---|---|---|---|
| Iris | 4 | 150 | 18 | 10 | 7 |
| Wine | 13 | 178 | 52 | 70 | 44 |
| Glass | 9 | 214 | 83 | 51 | 13 |

Table 2 shows the experimental result that was done at 200 for each methodology which is Fuzzy Ant, Initial SOM, and the proposed ASOM. There are three datasets for testing as follow: Iris, Wine, and Glass dataset. It can be seen that the proposed ASOM introduces the lowest of the number of error in classification for every datasets when compared to Fuzzy Ant and Initial SOM. This means that the proposed ASOM give a better performance in accuracy classification when compared to other methodologies.

Table 3: The result of Experiments with Iris Datasets.

| ***Method*** | ***Err. Class1*** | ***Err. Class2*** | ***Err. Class3*** | ***Avg. Acc. Rate*** | ***Max. Acc. Rate*** |
|---|---|---|---|---|---|
| Int. SOM | 3 | 22 | 9 | 76.31 | 91.25 |
| ASOM | 0 | 10 | 6 | 88.30 | 95.33 |
| ***diff*** | **3** | **12** | **3** | **11.99** | **4.08** |

Table 4: The result of Experiments with Wine Datasets.

| ***Method*** | ***Err. Class1*** | ***Err. Class2*** | ***Err. Class3*** | ***Avg. Acc. Rate*** | ***Max. Acc. Rate*** |
|---|---|---|---|---|---|
| Int. SOM | 24 | 13 | 39 | 56.92 | 60.67 |
| ASOM | 9 | 12 | 25 | 68.56 | 75.28 |
| ***diff*** | **15** | **1** | **14** | **11.64** | **14.61** |

Table 5: The result of Experiments with Glass Datasets.

| ***Method*** | ***Err. Class1*** | ***Err. Class2*** | ***Avg. Acc. Rate*** | ***Max. Acc. Rate*** |
|---|---|---|---|---|
| Int. SOM | 0 | 51 | 77.57 | 77.57 |
| ASOM | 11 | 33 | 78.96 | 93.93 |
| ***diff*** | **11** | **18** | **1.39** | **16.36** |

In table 3 shows that ASOM can decrease number of error in each class of Iris datasets when compared with traditional SOM. In addition, ASOM and SOM introduces 88.30 % and 76.31 % of the average of accuracy rate, respectively. This means that the proposed ASOM can increase accuracy rate when compared with SOM up to 11.99 %. Moreover, it can be seen that ASOM and SOM introduces 95.33 % and 91.25 % of the maximum average of accuracy rate, respectively. In other words, the proposed ASOM increases the maximum average of accuracy rate when compared with SOM up to 4.08 %.

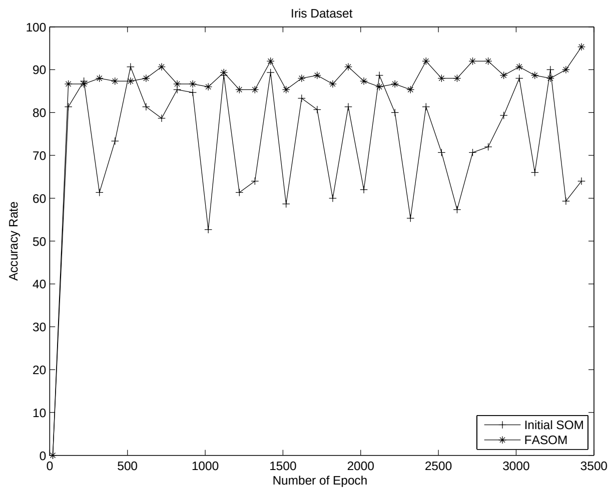


Fig. 5 Comparisons accuracy rate Initial SOM and ASOM

The figure 5 shows a comparison of the accuracy rate in case of the Iris. This experiment was done for 20-4000 epochs. It can be seen that ASOM gives an accuracy rate at 80-90 while SOM introduces an accuracy rate at only 50-90. In other words, the proposed ASOM introduces a better performance in the accuracy rate when compared with SOM.

The result shows that the data could not be separated distinctly. After random initialization was done, the data was more distinct separated. By using the proposed ASOM, those datasets could be precisely separated when compared with traditional SOM.

Experimental result with Wine datasets presents accuracy rate of Initial SOM and ASOM Algorithm as shown in a table 4. It can be seen that ASOM can decrease number of error in each class of Wine datasets when compared with traditional SOM. In addition, ASOM and SOM introduce 68.56 % and 56.92 % of the average of accuracy rate, respectively. . In other words, the proposed ASOM can increase accuracy rate when compared with SOM up to 11.64 %. Additionally, it can be seen that ASOM and SOM introduces 75.28 % and 60.67 % of the maximum average of accuracy rate, respectively. This means that the proposed ASOM increases the maximum average of accuracy rate when compared with SOM up to 14.61 %. From these result, it can be seen that distribution of wine datasets with weight from Initial SOM leads to the incorrect weight while ASOM can introduce the correct weight better than Initial SOM.

Table 5 shows the experiment result of the glass dataset.

It can be found that ASOM and SOM introduce the number of error in classification for first class 11 and 0, respectively. And the number of error in classification for second class 33 and 51, orderly. It should be noted that the glass dataset has 163 samples in the first class and has 51 samples in the second class. This means that initial SOM can't separate the data set into two classes. It classifies all input data into the first class while the proposed ASOM can separate the input data into two classes. Therefore, the proposed ASOM introduce a better performance in classification when compared with initial SOM. Additionally, ASOM and SOM give 78.96 % and 77.57 % of the average of accuracy rate, respectively. This means that the proposed ASOM can increase accuracy rate when compared with SOM up to 1.39 %. In addition, it can be seen that ASOM and SOM introduces 93.93 % and 77.57 % of the maximum average of accuracy rate, respectively. This means that the proposed ASOM increases the maximum average of accuracy rate when compared with SOM up to 16.36 %.

From experimental result of the glass dataset, it proves that Initial SOM allows all data converge to only one weight and results in classification all data into only the same class. It also confirms that ASOM can avoid the local minimum problem.

## 5. Discussion

For Iris Plant Datasets, this data set contains information about different types of Iris flowers. The data set consists of 150 examples each with four numeric predictive attributes. The data set contains 3 classes of 50 examples each, where each class refers to a type of Iris plant. One class is linearly separable from the other 2; the others have some overlap. Each Attribute is continuous attributes which is not between 0 and 1 but value of attribute range from 0.10 to 7.90. Therefore, the initial weight from randomize by minimize value or value 0 to 1 because the weight cannot convergence to control all group data. For winner node in the first time will update weight with distance data and weight which make be winner forever. This is because another weight cannot winner the first value of another weight far from data. This means that it is more distance than the first so the winner weight has only one present in the figure.

For Wine datasets, in this datasets consists of 178 examples each with 13 continuous attributes. The data set contains 3 classes with the following class distribution class 1 has 59 examples class 2 has 71 examples class 3 has 48 examples. All data in a mixture, combined elements lose their individual identities and are fused, are difficult to determine class correctly and clearly because each data have nearest distant for each attribute.

For Glass datasets, in these datasets contains 2 classes with the following class distribution: the first class 1 has 163 examples and the other class has 51 examples. The number of samples in the first class has more than 70 % of all samples. This allows opportunity of random which come from the first group to be more possible. And this leads the Initial SOM to make winner weight just only one. The proposed ASOM algorithm has the pheromone to keep statistic of weight updating. Although weight from random data is the same class, the ASOM algorithm can change weight from new random data until weight is converged to need weight which can represent all correct data. The proposed ASOM has the pheromone and $T_{create}$ for controlling the number of data.

From experiment, the Initial weight by the approach of the exchanging node gives a good performance but it is not the best. This is because weight initialization may be obtained from the same group dataset. Therefore, with new approach of ASOM, the weight initialization random from input node is selected by the probability of loading which is applying from Fuzzy Ant Clustering [14-23] and principle of Initial of Fuzzy C mean. This is a good solution for the good initialization weight. However, the good initialization weight is just the start of training, when training without evaluate not good for result. This paper proposes to evaluate by using $T_{create}$ which is applied from Fuzzy Ant Clustering. This method is normally used for evaluating convergence of data. $T_{create}$ can scope data requirement of probability of target which all technique can separate data correctly as shown in the figure 5.

## 6. Conclusion

In this paper, the proposed ASOM for data clustering method based on Fuzzy Ant and Self-Organize map is presented. A proposed original idea is that lost node is recoverable to overcome the problem of a single winner node by exchanging from new datasets. With the proposed methodology, traditional normalizing features with value in range of 0 and 1 are replaced by using initial weight from random input data. This enables the initial value to be related to the input datasets. Therefore, a problem of a single winner node leading to miss of clustering is alleviated. Additionally, lost nodes which have pheromone values less than a given threshold are re-initialized by randomizing from new datasets. This results in avoiding a problem of local minimum.

Experimental results confirm that the proposed ASOM can be used for both normalized and non-normalize data. In case of complexity e.g. overlap data, the ASOM has a better performance when compared with traditional SOM. In addition, the proposed technique has only one parameter which is a non-complexity technique. Evaluation of ant by the proposed threshold ($T_{create}$) will confirm the number of data in group which you may guess that near probability of target.

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