3D SOM Initialization Pattern Dictionary Algorithm Based on FCM Clustering

Ruihua Dong *, Xueyan Zhang and Hongsong Li

School of information and communication, Guilin University of Electronic Technology, Guilin, Guang xi, 541000, China

*Corresponding author’s e-mail: 1582464715@qq.com

Abstract. Aiming at the problem that the three-dimensional SOM reconstruction effect of the traditional pattern dictionary initialization algorithm is sensitive to the input order of the pattern, a three-dimensional SOM initialization mode dictionary algorithm based on FCM clustering is proposed. Calculate the mean square error of the training vector set and use the FCM algorithm to aggregate the resulting mean square differences into three categories. The average values are arranged in ascending order, and a certain pattern is extracted in the training vector at the same interval to form an initial pattern dictionary. The experimental results show that the 3D SOM initialization mode dictionary algorithm based on FCM clustering reduces the search time, increases the source matching degree, and improves the overall performance of the 3D SOM algorithm.

1. Introduction

In recent years, multimedia technology has developed rapidly. With the popularization of platforms such as Weibo and Ins, people pay more attention to news, technology, entertainment and other information. Images and videos are widely distributed throughout the world as important carriers of information. However, for the communication system, behind this convenience and enjoyment is coming large data transfer volume, faster and faster transfer speed requirements. Therefore, searching for more efficient data compression technology is imminent.

Self-Organizing Mapping (The SOM) algorithm is an efficient clustering algorithm [1]. It has been applied in many fields, such as neural computing, data mining, clustering, artificial intelligence, speech recognition, vector quantization [2]-[12]. It also provides a new approach for image compression [13]-[14]. It automatically trains its corresponding feature pattern dictionary by learning the image samples, and the receiver only needs to map according to the pattern dictionary and address. It is possible to recover the original image with high efficiency and high compression ratio, which has obvious advantages. The key to the SOM algorithm is the establishment of the pattern dictionary. A good initialization mode dictionary will significantly improve the overall performance of the algorithm. Therefore, it is of great significance to continuously optimize the pattern dictionary initialization algorithm. Current classic the initialization mode dictionary has a random extraction method, a split method and an average separation method, which are simple and practical but have low mode utilization and limited source matching rate. To this end, a construction method based on FCM cluster initialization mode dictionary is proposed to improve the utilization of the mode and the source matching degree, and improve the performance of the self-organizing mapping algorithm.
2. Self-Organizing Mapping

SOM simulates the self-organizing feature mapping function of the brain's nervous system, and it is a feedforward network of unsupervised competitive learning. The topology of SOM network is shown in Fig.1. The topology is divided into two layers: the input layer and the output layer, where the output layer is also known as the mapping layer or the competition layer. There is no hidden layer between the two layers. The function of input layer is to perceive signals and the function of output layer is to output classifications.

Figure 1. Network structure of SOM

The SOM algorithm consists of two processes: establishing pattern library and training mode library. One-dimensional input and two-dimensional output are generally used when building a pattern library. However, such network structure cannot directly deal with 3D signals, so 3DSOM network is introduced in this paper, and the network structure of 3DSOM is shown as Fig.2. Three-dimensional structure can not only deal with 3D signals more efficiently, but also can get better reconstruction effect in image compression.

Figure 2. Network structure of 3DSOM

2.1. Traditional pattern dictionary initialization algorithm.

The pattern dictionary establishment methods of the traditional SOM algorithm are commonly used: random extraction method, split method and average separation method.

(1) Random extraction method

If the mode dictionary specification is N, N patterns are randomly extracted from the training vector set in order according to a specific structure. The columns are stored so that they are constructed into an initial pattern dictionary, and the number of selected pattern vectors must be less than the training vector set. The random extraction method is simple and efficient, but the mode vector utilization is low, resulting in poor performance of the pattern dictionary.

(2) Splitting method

Calculate the quality of all vectors in a given training vector set. And use the centroid as the first mode vector of the initial pattern dictionary; then select a parameter multiplied by the first mode vector to obtain the second mode vector, and use LBG algorithm to design the pattern containing the above two pattern vectors. Dictionary; then choose a suitable parameter multiplied by the two previously
obtained vector, four pattern vectors are obtained, a pattern dictionary containing four pattern vectors is designed by the LBG algorithm; and so on, until a pattern dictionary containing N patterns is formed. The pattern dictionary constructed by the split method has excellent performance, but its generation process is computationally intensive, computationally complex, and sensitive to multiplicative parameters. Unstable.

(3) Average separation method
If the size of the pattern dictionary is N, all vectors are divided into N segments in order, the length of each segment is: \( P = L / N \). L is the size of the training vector set; the average of the vectors in each segment is taken as the pattern vector of the initial pattern dictionary to generate an initial pattern dictionary. The average separation method discards the randomness of the original random method and finds the vector to form the initial pattern dictionary according to certain rules, which greatly improves the utilization of the pattern vector and improves the performance of the final pattern dictionary.

2.2. SOM-based pattern dictionary construction
The construction scheme is as follows:

(1) Set the specification of SOM network as \( (N,M) \), the N is the initialization dictionary specification, M is the specification of the initialization dictionary model.

(2) Divide the input image samples according to the set size M without repeat segmentation, and make it into L sample pieces; \( Y(t), t = 0,1,2,...,L-1 \)

(3) According to the distance from \( L/M \). Select N modes from the order \( Y(t) \), normalize the mode, and arrange the normalized mode combination into a three-dimensional network form as an initialization dictionary \( D_j(0), j = 0,1,2,...,N-1 \).

(4) Assign the initial neighborhood range: \( N_j(0), j = 1,2,...,N \).

(5) Choose a brand new sample: \( Y = (y_1, y_2,..., y_m)^T \).

(6) The distortion metric similarity criterion uses the mean square error measure. In the initial stage of training, the distortion measure distance of each model to be trained and the independent mode feature similarity in the initialization dictionary is respectively estimated, and the mode with the shortest distance from the sample to be trained is best similar mode, ie:

\[
  r_j(t) = \min_{0\leq j \leq N-1} r_j(t)
\]

(1)

(7) Update the winning mode \( j^* \) and the mode weights in its neighborhood range \( N(t) \) according to (2),

\[
  W_j(t+1) = \begin{cases} 
  W_j(t) + \alpha(t)[X(t) - W_j(t)], & j \in j^*, N_j(t) \\
  W_j(t), & \text{others}
  \end{cases}
\]

(2)

In the above formula, it is a neighborhood function, generally using a monotonically decreasing exponential function, which is the closest range of the activated mode, and is the farthest range of the activated mode. The number of cycles. In the process of updating the mode dictionary, the neighborhood range is set farther. As the samples to be trained continuously match the iterations, the network training tends to be stable, and only the weights of the activated modes need to be finely adjusted. For the learning function, the exponential function is usually also selected, which is the maximum value of the initial stage weight update, which is a constant.

(8) Return to step (4) again until all input samples complete the learning, training, and output mode dictionary in the initialization dictionary.

3. FCM-based pattern dictionary initialization algorithm

3.1. FCM algorithm
Fuzzy c-means algorithm (FCM) [15-17]. The application needs to update the training data in real time, estimate the membership degree of each training data and all category center points, and finally determine the category attribute of each data to achieve the goal of automatic classification of data. The
biggest feature of the algorithm is the classification of categories with ambiguity, that is, each given data weight is at (0, 1). The degree of fit determines the distance between each data and the center point. The objective function and constraints of the algorithm are:

\[ J_f = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m \| x_j - c_i \|^2 \]

\[ \sum_{i=1}^{c} \mu_{ij} = 1, \quad j = 1, 2, \ldots, n \]

In the above formula, \( \mu_{ij}^m \) represents the membership limit of the i-th data weight corresponding to the j-th category, \( m \) is a limiting factor, \( c_i \) represents the center of the first category, \( \| x_j - c_i \|^2 \) is a constraint. Calculating the extremum of the function to be solved usually uses Lagrange number multiplication to substitute the constraint into the function to be solved. Then (3) is transformed into:

\[ J = \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m \| x_j - c_i \|^2 + \lambda_1 (\sum_{i=1}^{c} \mu_{i1} - 1) + \lambda_2 (\sum_{i=1}^{c} \mu_{i2} - 1) + \ldots + \lambda_{m} (\sum_{i=1}^{c} \mu_{im} - 1) \]

Determine the membership degree and the center point in (5), respectively, to obtain the center point:

\[ C_i = \frac{\sum_{j=1}^{n} (\mu_{ij})^m x_j}{\sum_{j=1}^{n} \mu_{ij}^m} \]

It is obvious that the membership degree is related to the center point, so one of the parameters of the membership degree or the category center point is assigned in the initial stage of the algorithm, and one parameter is used to solve the other parameter. The objective function will change in real time during the update phase. As the iterative optimization process continues, the required solution. The number does not change any more, and the solution to be solved obtains a relatively stable solution, that is, if the equation (3) is smaller than the set threshold, the algorithm stops. The algorithm fully considers the reliability of the sample classification. When the sample has an absolute advantage to the membership of an attribute, the sample is very stable in all categories.

3.2. New initialization mode dictionary construction scheme

(1) For raw data pattern sets; \( Y(t), t = 0,1,2, \ldots, L - 1 \), find the mean square error of each mode.

(2) The FCM clustering method is used to cluster the obtained data into classes (the number of clusters is far less than the number of samples), and the mean squared variance of each category is sorted in ascending order: \( Y_1(t), Y_2(t), \ldots, Y_L(t) \).

(3) According to the selected initial dictionary specification \( N \), \( N \) patterns are respectively extracted from the \( Y_i(t), Y_j(t), \ldots, Y_k(t) \) according to the distances \( L/N \) to form an initial dictionary based on the feature classification.

4. Experiment

The experiment is based on the random method and the initialization dictionary construction of the F-FCM algorithm, and the image coding is applied for performance comparison. Experimental image select: Lena, Boat, The mode specification is \( 8 \times 8 \), the image compression ratio \( C_R = (M \times B_0) / B_c \), \( M \) is the dictionary mode specification, \( B_0 \) is the number of bits of the pixel in the test object, \( B_c \) is the mode specification address bit number. When the mode dictionary specification is 2048, \( C_R \) is 46.5; when the mode dictionary specification is 1024, \( C_R \) is 51.2; when the mode dictionary specification is 512, \( C_R \) is 56.8, when the mode dictionary specification is 258, \( C_R \) is 64. The Peak Signal to Noise Ratio (PSNR) is used as an objective evaluation criterion for reconstructing image performance:
\[PSNR = 10\log \frac{255^2}{E_{MSE}} \text{ dB}\]  
\[(7)\]

\(E_{MSE}\) in above is the mean square error between the test image sample and the dictionary-based reconstruction image, image compression performance is shown in Table 1 and Table 2.

Table 1. Lena Image compression performance comparison based on different SOM dictionary initialization algorithms.

| Compression ratio | Random method /dB | FCM algorithm /dB | Effect improvement /dB |
|-------------------|-------------------|-------------------|------------------------|
| 46.5              | 36.0685           | 38.9312           | 2.8627                 |
| 51.2              | 33.2503           | 34.4856           | 1.2353                 |
| 56.8              | 30.7351           | 30.9893           | 0.2542                 |
| 64                | 28.6390           | 28.8268           | 0.1878                 |

Table 2. Boat Image compression performance comparison based on different SOM dictionary initialization algorithms.

| Compression ratio | Random method /dB | FCM algorithm /dB | Effect improvement /dB |
|-------------------|-------------------|-------------------|------------------------|
| 46.5              | 33.5567           | 36.7666           | 3.2099                 |
| 51.2              | 30.9500           | 31.9903           | 1.0403                 |
| 56.8              | 28.6305           | 28.6618           | 0.0313                 |
| 64                | 26.9221           | 26.9381           | 0.0160                 |

Experiments show that the SOM algorithm based on feature clustering is constructed. When the dictionary is implemented, the image reconstruction performance is relatively good. It is found that the performance of reconstructed image has a certain relationship with the dictionary specification. When the specification is large, the reconstructed image performance is better. When the specification is small, the reconstructed image is relatively poor. When the FCM algorithm processes big data, the clustering effect is more obvious. It is assessed that the pattern dictionary constructed by the SOM algorithm based on FCM clustering is superior in the performance of image compression. For the Lena image reconstruction effect, when the compression ratio is 46.5, the performance of the image dictionary constructed by the SOM algorithm based on FCM clustering is 3.2099dB better than that of the random method. 8627dB. For the Boat image reconstruction effect, the performance of the image dictionary constructed by the SOM algorithm based on FCM clustering is 3.2099dB better than the random method.

5. Conclusion

The traditional 3D SOM initialization mode dictionary algorithm preserves the topology of the original data when establishing the pattern dictionary, and the adjacent mode weights are bound to be affected. SOM algorithm based on FCM is studied. FCM algorithm is used to preprocess the pattern vector and establish the ordered initial pattern dictionary, which reduces the damage caused by weight adjustment to the surrounding image blocks, protects the diversity of patterns, shortens the search time and improves the performance of SOM algorithm.
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