Unsupervised Learning Approach for Clustering Leaf Images

G Chamundeswari
Research Scholar, JNTU Kakinada, Kakinada, A.P., India.

Abstract. With appropriate representation methods, the clustering techniques are found to be efficient with neural networks. The present work aims to propose various feature representation techniques for efficient clustering. The methods used for feature representation in this paper are, a method using random closed set, a method using edge information of input entity, a method that uses Huff transformation and a method that uses boundary moments. A comparative study of these representation methods for clustering the input objects using artificial neural networks, specifically Self-Organizing Map (SOM) is focused.

Keywords – Feature vector, Self Organizing Maps (SOM), Clustering, Neural Networks.

1. Introduction
Clustering is the process of grouping similar objects that have same characteristics. Objects belonging to a cluster have high similarity and are dissimilar to objects of other clusters. Clustering technique [3] needs efficient representation methods. Image segmentation [5] involves the process of dividing the image into segments or regions having similar attributes or characteristics like intensity or texture, colour etc., so as to analyse the acquired information. Using these features the leaf images are clustered. The present work aims to propose appropriate combinations of various representation techniques with Self Organizing Maps (SOM) for future performance. The neural networks work on the model of a human brain. In neural networks the neurons are clustered based on the active neurons by reinforcing the neighbours of the active neurons and suppressing the remaining neurons. The distinct property of SOM is that they can map high dimensional input vectors into spaces with fewer dimensions and preserve the original topology [2]. The next section emphasises on the various representation methods. Among various techniques used, a Boundary Moment based Clustering Technique (BMCT) is used to represent the input image with the moment based feature vector. The second method - An edge based clustering technique is proposed for edge representation. In which, the identified segments of the image are enhanced using an enhancement filter for effective representation. After which, various sub images and edge image are generated. Features are computed for every sub-image and the edge image. In the third method – contact distribution function based clustering technique is proposed for random closed set representation. In this method, the spherical contact distribution function based feature vector, which gives the neighborhood connectivity representation is considered as the input object. The fourth method – line segment based clustering is an approach for evaluating the feature vector which is proposed with the Hough transformation. With the Hough transformation, the points are mapped to the line segment. The line features are considered as the feature vector. In all these methods, the extracted features are further utilized for clustering using Self Organizing Map (SOM). In SOM based clustering technique the evaluation of features is found to be
crucial. The related work is given in second section, methodology in the third and the experimental observations and results are given in the fourth section.

2. Related Work
Grouping of similar objects by splitting up of data is referred to clustering objects that are similar to one another and dissimilar to the objects in other groups, are contained in every group or cluster. Reduction of intra cluster distance [24, 19], maximizing inter cluster distances is the objective. For pattern recognition applications, the data clustering is found to be a crucial stage [13]. Ensemble based clustering method [16] is used to improve the reliability of the clustering method.

It is found that, in computer vision and recognition of patterns, clustering is one of the most interested research areas. To perform the clustering process, various approaches and techniques are available in the literature [23, 20]. Because of the wide variety of applications like segmentation, content based information retrieval and object recognition, it has gained high attention by the researchers. The difficult task is the search of relevant information [17] in unsupervised approach. For solving the combinational optimization problem, a Multi-Cluster Feature Selection (MCFS) approach is used. Using neuro morphological approach [18], the neostriate inter neurons are clustered. The predictor is estimated by it and then analysis of multivariate clusters is performed and then classified into multi labels. An ensemble of clustering tree [21] is used to improve the efficiency of the fuzzy min-max [14] network. An efficient learning model is used by it to improve the performance of the clustering method. Four different types of mean measures are used in the network. To cluster the fuzzy mid-wave infrared image, a multilayer immune network [25] is used. The mechanism of the coordination network is used by this. With the immune network, the inter class variance is minimized by it. It is found that the low performance is yielded when compared with other networks by the Euclidean distance based clustering with ART2 network [26]. A steganographic project with the hybrid neural system [15] is used to improve this. The performances of both ART2 and RBF networks are used by it. It is observed that, for analyzing the dynamic patterns, the unsupervised neural network [22] is found to be effective. To analyze the data with the clustering techniques SOM is used.

3. Methodology
The clustering techniques require the efficient representation of the input image. For this, the present work compares the various methods proposed like, a boundary moment based clustering technique (BMCT) [8], an edge based clustering technique (ECT) [9], a contact distribution function based clustering technique (CDFCT) [10], and line segment region representation based clustering technique (LSCT) to give a better choice. The flow chart is as shown in figure.1.

![Figure 1. Flowchart for the methodology](image)

A database consisting of 795 leaf image samples from 90 different plant species ranging from 2 to 25 is taken for experimenting.
3.1. Boundary Moment based Clustering Technique with SOM
Hu in 1992 gave the mathematical foundation for 2D moment invariants, which were found to be quick and highly reliable. These moment invariants are invariant with respect to translation, scale and orientation. A boundary moment based clustering technique (BMCT) in which the boundary of the input image is represented with the moment based feature vector. The boundary of the input image is used for this. Seven invariant features will be evaluated from the boundary of the image, as shown in (1).

\[ \mu_{pq} = \sum_{x} \sum_{y} \left( x - \bar{x} \right)^{p} \left( y - \bar{y} \right)^{q} f(x,y) \]  

(1)

The invariance is achieved by computing moments that are normalized with respect to the centre of gravity i.e., the centre of mass of the distribution is at the origin, which are called the central moments. Seven-moment invariant descriptors are formulated as a feature vector. The SOM is used to perform the process of clustering.

3.2. Edge based Clustering Technique with SOM
To reduce noise and smoothen the image, mean filter is used. Each pixel is replaced with the average of its neighbouring pixels. A local window is considered, of 3 X 3 size as shown in Table 1. The pixels (p1, p2, p4) present to the left top corner of this window are used by this filter as shown in (2).

|   | P2 | P3 |
|---|----|----|
| 1 |    |    |
| 4 | P5 | P6 |
| 7 | P8 | P9 |

**Figure 2.** A Local window for the pixel P5

\[ F = (A \times P_1 + P_3) - (B \times P_1) + (C \times P_3 - [D \times (P_1 + P_3)]) + [D \times P_1] \]  

(2)

Using (3)-(7), the edge image and the sub images are generated

\[ S_1 = F_{p_1} - F_{p_3} \]  

(3)

\[ S_2 = F_{p_1} - F_{p_3} \]  

(4)

\[ S_3 = F_{p_1} - F_{p_3} \]  

(5)

\[ S_4 = F_{p_1} - F_{p_3} \]  

(6)

\[ E = \begin{cases} 1 & \left( \sum p_i \right) > 1 \\ 0 & \text{otherwise} \end{cases} \]  

(7)

A co-occurrence matrix is generated for each of the edge and sub images. The co-occurrence matrix is a statistical texture analysis method that examines the relationship among the pixels and defines how frequently the combination of pixels are present in the image in a given direction and distance. The feature vector consists of the five features extracted and are then evaluated in the next stage of clustering using SOM.

3.3. Methodology of CDF Based Clustering Technique with SOM
For the texture based object recognition, there are many standard features [6] and random closed sets is one such used in this approach. Random closed set (RCS) can be used as univariate RCS for binary images and multivariate for gray scale images. This representation is described with various features like volume fraction, covariance, cross covariance, Ripley’s function and contact distribution. It is found that the contact distribution function based feature vector is efficient for object recognition. The contact distribution function can be either spherical or linear.
Let S be the random closed set and the window is T then the volume fraction (VF) in (8) indicates the area or volume of the window

\[ VF = \frac{|S \cap T|}{|T|} = \frac{v(S)}{v(T)} \]  

(8)

The covariance (CV) of the S with increasing size t is given in (9).

\[ CV(t) = \frac{|S + t \cap (T + t)|}{|T + t|} = \frac{v(S_{(t)})}{v(T_{(t)})} \]  

(9)

The Spherical contact distribution function (SCDF) of S with a ball of radius t centered at the origin is given in (10).

\[ SCDF(t) = 1 - \frac{v(S_{(t)})}{v(T_{(t)})} \]  

(10)

In [11], these features are used to describe the binary texture efficiently. For clustering, SOM is observed to be efficient.

3.4. Line Segment Region Representation Based Clustering Approach with SOM

The borders between the regions are separated with different grey levels by line segments. The input image must be a thresholded edge image which is calculated using sobel operator. The line segment will be estimated with various angles from 0° to 360° using Huff-transformation. With ‘n’ pixels, the set of pixels that make up straight lines are found.

\[ b = -xa + y \]  

(11)

A single point in X-Y plane gives a line in (a,b) space. With the peaks, the lines are identified and the length of the detected lines are considered as features, which are clustered further using SOM neural network.

4. Results

The experiment has been conducted using different SOM organizations namely grid topology, random topology, triangle topology and hexagon topology. The proposed methods are experimented with various sizes of neighborhoods varying for 3 to 20, whose performance is evaluated for each structure of the topological pattern. In this experiment four measures are used to calculate the distance- The boxdist is the distance given by the position vector of the neuron layer, linkdist is the number of links associated by a neuron, dist is the distance given by the Euclidean measure computed and finally the mandist is the distance given by the Manhattan measure. For each experiment conducted with SOM, associated structure of the topology, the size of the neighborhood, the calculated distance measure and the feature vector is fed.

A confusion table is used to evaluate the performance of a classifier. Wherein the predicted and the actual class labels are compared and the results are measured to evaluate and measure the level of performance of the proposed method, four measures are used, the false positive ratio (FPR), the false negative ratio (FNR), the true positive ratio (TPR) and the true negative ratio (TNR).

For example the following figures 3, 4, 5 and 6 demonstrates TPR representing all the topology structures, with varying neighborhood sizes and the four mentioned distances that are calculated. By this observation the TPR is at its highest for randtop topology.
**Figure 3.** SOM-Hextop-TPR Comparison Result

**Figure 4.** SOM-Randtop-TPR Comparison Result

**Figure 5.** SOM-Tritop-TPR Comparison Result
In this work the extracted feature vectors is scaled to 1. The result achieved with SOM on various topologies is the normalized one.

The performance measures that are evaluated for Hextop structure of SOM and neighborhood size=3 with Euclidean distance measure of all the methods BMCT, ECT, CDFCT and LSCT are shown in Table 1.

### Table 1. Performance evaluation of BMCT

| METHOD | FNR        | FPR        | TPR        | TNR        |
|--------|------------|------------|------------|------------|
| B      | 0.01194    | 0.003035   | 0.952521   | 0.988806   |
| MCT    | 0.010966   | 0.025160   | 0.974840   | 0.989034   |
| E      | 0.0        | 0.0        | 0.0        | 0.0        |
| C      | 0.0        | 0.0        | 0.0        | 0.0        |
| DFCT   | 0.010999   | 0.007640   | 0.925693   | 0.988901   |
| L      | 0.0        | 0.0        | 0.0        | 0.0        |
| SCT    | 0.011119   | 0.017244   | 0.982756   | 0.98881    |

4.1. Comparison of Methods
The various performance metrics used in the comparisons of the proposed methods are Precision and F-Measure. Precision gives the number of correct predictions. The best precision is 1 and the worst is 0. The F measure gives the accuracy when there are uneven class distributions. Similarly the best F measure is 1 and the worst is 0.

Comparing the results of the following four methods with Hexagonal topology, Euclidean distance and neighbourhood size 3, we can conclude that Edge based clustering method (ECT) is more efficient than the remaining three methods as shown in Table 2.

### Table 2: Comparison of various methods

| METHOD | PRECISION | FMEASURE |
|--------|-----------|----------|
| BMCT   | 0.99      | 0.99     |
| ECT    | 1         | 0.98     |
| CDFCT  | 0.99      | 0.989    |
| LSCT   | 0.98      | 0.985    |

5. Conclusion
The present work is the effort of quantifying the representation of the input, so that it is more efficient for interpretation using SOM. Of the various methods proposed the BMCT, ECT, CDFCT and LSCT,
the ECT is found to be more efficient. The proposed methods can be further extended with the deep neural networks for getting finer clustering results.

**References**

[1] A. W. P. Fok, H. S. Wong and Y. S. Chen, "Hidden Markov Model Based Characterization of Content Access Patterns in an e-Learning Environment," 2005 IEEE International Conference on Multimedia and Expo, Amsterdam, 2005, pp. 201-204.

[2] Kohonen.T, "The Self-Organizing Maps," Third Ed., Springer, Germany, 2000.

[3] J. Li, D. Li and Y. Zhang, "Efficient Distributed Data Clustering on Spark," 2015 IEEE International Conference on Cluster Computing, Chicago, IL, 2015, pp. 504-505.

[4] R. Nock and F. Nielsen, "On weighting clustering," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 8, pp. 1223-1235, Aug. 2006.

[5] S. D. Pandya and P. V. Virparia, "Comparing the application of classification and association rule mining techniques of data mining in an Indian university to uncover hidden patterns," 2013 International Conference on Intelligent Systems and Signal Processing (ISSP), Gujarat, 2013, pp. 361-364.

[6] T. Jabid, M. H. Kabir and O. Chae, "Gender Classification Using Local Directional Pattern (LDP)," 2010 20th International Conference on Pattern Recognition, Istanbul, 2010, pp. 2162-2165.

[7] Yi Tan and Guo-Ji Zhang, "The application of machine learning algorithm in underwriting process," 2005 International Conference on Machine Learning and Cybernetics, Guangzhou, China, 2005, pp. 3523-3527 Vol. 6.

[8] G.Chamundeswari, G.Partha Saradhi Varma and Ch. Satyanarayana, "SOM based Clustering Technique with Boundary Moments," Proceedings of the International Conference on Intelligent Computing and Sustainable System, Coimbatore. DVD Part Number: CFP18003-DVD; ISBN: 978-1-5386-4344-0.

[9] G. Chamundeswari, G. P. S. Varma, Ch. Satyanarayana, "Contact Distribution Function based Clustering Technique with Self-Organizing Maps", International Journal of Image, Graphics and Signal Processing(IJIGSP), Vol.10, No.3, pp. 9-17, 2018. DOI: 10.5815/ijigsp.2018.03.02

[10] G. Chamundeswari, G. P. S. Varma, Ch. Satyanarayana, "An Edge based Clustering Technique with Self-Organizing Maps", International Journal of Information Technology and Computer Science(IJITCS), Vol.10, No.5, pp.30-39, 2018. DOI: 10.5815/ijitcs.2018.05.03.

[11] Irene Epifanio, Guillermo Ayala, “A Random Set View of Texture Classification,” IEEE Transactions on Image Processing, Vol. 11, No. 8, August 2002, pp. 859-867.

[12] Brewster E., Keller J.M., Popescu M., "A new approach for extracting texture features to aid detection of explosive hazards using synthetic aperture acoustic sensing," Proceedings Volume 10182, Detection and Sensing of Mines, Explosive Objects, and Obscured Targets XXII; 101821F (2017).

[13] Abdelkarim Ben Ayed , Mohamed Ben Halima , Adel M. Alimi, "Adaptive fuzzy exponent cluster ensemble system based feature selection and spectral clustering," IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 1-6, 2017.

[14] B. Goswami, G. Bhandari and S. Goswami, "Fuzzy min-max neural network for satellite infrared image clustering," 2012 Third International Conference on Emerging Applications of Information Technology, Kolkata, 2012, pp. 239-242.

[15] Andrzej Bielecki, Mateusz Wójcik, “Hybrid system of ART and RBF neural networks for online clustering,” Applied Soft Computing, Volume 58, September 2017, Pages 1-10.

[16] Dong Huang, Chang-Dong Wang, Jian-Huang Lai,"Locally Weighted Ensemble Clustering,” IEEE Transactions on Cybernetics, Volume: 48, Issue: 5, 1460-1473, 2018.
[17] Cai, Deng and Zhang, Chiyuan and He, Xiaofei, “Unsupervised Feature Selection for Multi-cluster Data,” Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2010, 333-342.

[18] Ivan Grbatinić, Nebojša Milošević, Bojana Krstonošić, “The neuromorphological caudate–putaminal clustering of neostriate interneurons: Kohonen self-organizing maps and supervised artificial neural networks with multivariate analysis,” Journal of Theoretical Biology, In Press, Accepted Manuscript, Available online 21 November 2017.

[19] J. Li, D. Li and Y. Zhang, "Efficient Distributed Data Clustering on Spark," 2015 IEEE International Conference on Cluster Computing, Chicago, IL, 2015, pp. 504-505.

[20] M. Steinbach, G. Karypis, V. Kumar, “A Comparison of Document Clustering Techniques,” In KDD Workshop on Text Mining, 2000.

[21] Manjeevan Seera, Kuldeep Randhawa, Chee Peng Lim, “Improving the Fuzzy Min–Max neural network performance with an ensemble of clustering trees,” Neurocomputing, In Press, Corrected Proof, Available online 7 November 2017.

[22] Marina Resta, Michele Sonnessa, Elena Tànfani, Angela Testi, “Unsupervised neural networks for clustering emergent patient flows,” Operations Research for Health Care, In Press, Corrected Proof, Available online 26 August 2017.

[23] Pavel Berkhin, “Survey of Clustering Data Mining Techniques,” In: Accrue Software, 2003.

[24] R. Nock and F. Nielsen, "On weighting clustering," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 8, pp. 1223-1235, Aug. 2006.

[25] Xiao Yu, “Fuzzy infrared image segmentation based on multilayer immune clustering neural network,” Optik - International Journal for Light and Electron Optics, Volume 140, July 2017, Pages 959-963.

[26] Y. Peng, S. Liu and Y. Zhang, "Indicator diagram identification based on ART2 neural network and features of moment invariant," 2012 2nd International Conference on Consumer Electronics, Communications and Networks (CECNet), Yichang, 2012, pp. 1075-1078.