Contact Distribution Function based Clustering Technique with Self-Organizing Maps

G. Chamundeswari[1]
[1] Research Scholar, Jawaharlal Nehru Technological University Kakinada, Kakinada, A.P., India.
Email: ijarichamu@gmail.com

Dr. G. P. S. Varma[2]
[2] Professor & Principal, SRKR Engineering College, Bhimavaram, A.P., India.
Email: gpsvarma@gmail.com

Dr. Ch. Satyanarayana[3]
[3] Professor, Dept. of CSE, UCE, Jawaharlal Nehru Technological University Kakinada, Kakinada, A.P., India.
Email: chsatyanarayana@yahoo.com

Abstract—Currently clustering techniques play a vital role in object recognition process. The clustering techniques are found to be efficient with neural networks. So, the present paper proposed a novel method for clustering the input objects with Self-Organizing Map (SOM). The proposed method considers the input object as a random closed set. The random set can be efficiently described with various features viz., volume fractions, co-variance and contact distributions etc. In the proposed method, the input object is described efficiently with spherical contact distribution. The proposed method is experimented with the leaf data set with 795 images. The performance of the proposed method is evaluated with various topologies of SOM and is measured with four measures viz., FNR, FPR, TPR and TNR. The results indicate the efficiency of the proposed method.

Index Terms—Spherical contact distribution, Linear contact distribution, Feature vector, Neighborhood and Topology.

I. INTRODUCTION

Currently, the researchers are focus on the design of efficient object recognition method. The object recognition methods can be applicable to various applications viz., surveillance systems, tumor detection, leaf or plant analysis etc. The object can be described with various features of shape, color or texture etc. An object recognition method by combining texture, color and shape features [1] is found to be efficient than Krawtchouk moments, Zernike moments, or Tchebichef moments. This method involves the computation of three different feature vectors. A method is designed for the fruit and vegetable recognition system [2]. It consists of three stages viz., background subtraction, feature extraction, and training and classification. The underwater recognition system [3] is designed with chain coding, texture and statistical features. The described feature vector is given to a learning algorithm for getting efficient result. A Mean Local Mapped Pattern (M-LMP) [4] is a descriptor designed based on visual code book. It performs analysis of appearance features of the object local patch. For diabetic patients, estimation of carbohydrate content in the meal is conducted by a food recognition algorithm. The bag-of-features (BoF) model [5] is used for the automatic recognition.

II. RELATED WORK

The Gaussian mixture model clustering technique [6] is used for object recognition. In this method, updated PageRank algorithm is used for detection of saliency points. Then the points are used for representing the input object. An approach for estimation of shape and position of an object [7] is proposed based on interpolating, data mining and steoreometric methods. The clustering stage involved in the proposed method is observed be complex. The clustering of Voting Lines (CVL) method [8] gets the direct consistent hypothesis with the combination of pair wise and weighted approach for clustering voting lines. It represents the object boundary with the sparse representation. The efficiency of the clustering based object recognition process can be increased with the boosting technique. The cluster based boosting (CBB) method [9] consists of outlier detection stage for enhancing the efficiency. For the object recognition method, it is observed that the depth information [10] play a vital role. Based on this, the clusters are efficiently formed and thus recognize the objects.

The self-organizing map (SOM) is with features used to recognize various human activities [11]. The features reflect the body joint features which are computed based on various distance measures. The emotion recognition

model [12] uses the feature vector of length 26. The feature vector is further processed by SOM for classification. The hand and full body is tracked [13] efficiently with the touch-free gesture technology. This technology along with the SOM is found to be efficient. The clustering techniques involved in the bankruptcy trajectory [14] uses two different types of SOMs i) feature SOM ii) trajectory SOM. The temporal features are analyzed with FSOM and clustering is performed with TSOM. Moving Average SOM [15] is found to be efficient for segmenting the medical images. The texture features are used widely used for object recognition. Local directional patterns [16] are one of the popular texture features. The local binary patterns [17] along with the K-NN and surf matching are used for recognizing the objects. The texture can be further described with the 2D local power spectrum [18]. The spectrum is generated with the Gabor filters. An object [19, 20, 21] can be represented with the random closed set and describes the object with various features and performs classification with distance measure. To improve the efficiency of the object recognition process, the present paper describes the input object with contact distribution based features and further analysis is performed with SOM.

The present paper is organized as follows. The section I give the introduction to the object recognition, section II discusses about the related work, section III discusses about the proposed methodology. The detailed results and discussion is provided in section III and the conclusions in section IV.

III. METHODOLOGY

The object recognition techniques are needed for various applications of computer vision and pattern recognition. Among various approaches for object recognition, the texture based methods are found to be simple and efficient. The Haralick based features are the standard texture features. Other than these, there are various standard features viz., Local Binary Pattern (LBP), Local Directional Pattern (LDP) etc.

The present paper considers an approach for representing the input object with random set. The random set can be used to represent both the binary and grey level images. For binary images, univariate random closed set is used for representation and for grey level images; multivariate random closed set is used. This representation of the object can be further described with various features viz., volume fraction, covariance, cross covariance, Ripley's function, contact distribution. It is found that the contact distribution function based feature vector is efficient for object recognition. So, the present paper considers the contact distribution based description of the input object. The contact distribution functions are used to describe the random spatial structures of the input object. The contact distribution function can be either spherical or linear. The present paper considers the spherical contact distribution function based feature vector for representing the input object.

Let S be the random closed set and the window is T then the volume fraction (VF) in (1) indicates the area or volume of the window.

$$VF = \frac{|S \cap T|}{|T|} = \frac{v(S)}{v(T)} \qquad (1)$$

The covariance (CV) of the S with increasing size t is given in (2).

$$CV(t) = \frac{(|S+t| \cap (T+t)|)}{|T+t|} = \frac{v(\in_{\{0,t\}}(S))}{v(\in_{\{0,t\}}(T))} \qquad (2)$$

The Spherical contact distribution function (SCDF) of S with a ball of radius t centered at origin is given in (3).

$$SCDF(t) = 1 - \frac{v(\in_{B(0,t)}(S^C))}{v(\in_{B(0,t)}(T))} \frac{v(T)}{v(S^C)} \qquad (3)$$

In [22], these features are used to describe the binary texture efficiently. They used distance measures for classification stage. To improve the accuracy of the recognition rate, the present paper uses the clustering technique. Among various clustering techniques, the self-Organizing Map (SOM) is observed to be efficient. So, the present paper uses SOM for the clustering stage. The topology of the SOM is shown in Fig. 1. The proposed method is experimented with the leaf data base which consists of 90 groups of images. So, the SOM is designed with the size 15×6 topology. The neighborhood connections of the designed SOM are shown in Fig. 2. The weight positions of the designed SOM are shown in Fig. 3.
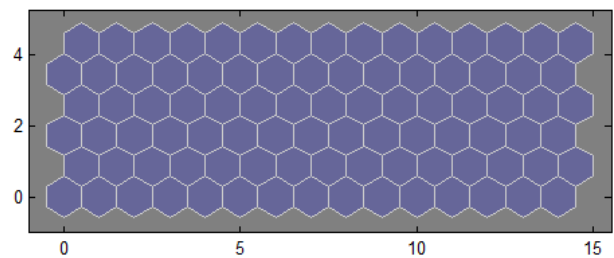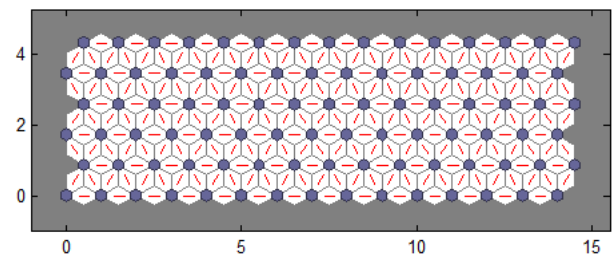

Fig. 1. SOM Topology.

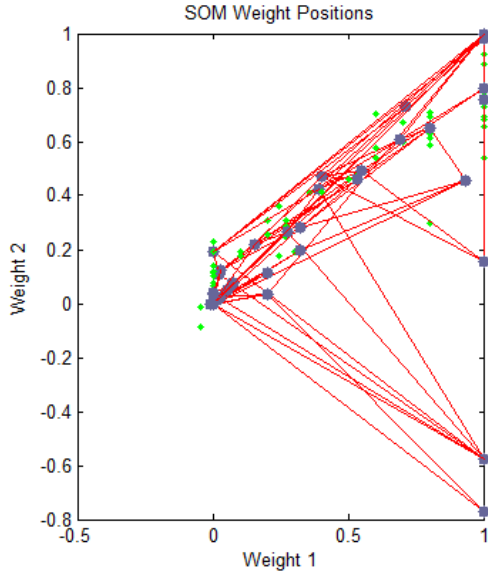Fig. 2. SOM Neighbor Connections.

Fig. 3. SOM Weight Positions.

IV. Results and Discussions

The present paper describes the input object with spherical contact distribution features. The described feature vector is given to SOM. The present paper evaluated the proposed approach with the leaf database of 795 images which are grouped into 90categories. The present paper has conducted the experiment with four different SOM organizations viz., Hextop, Randtop, Tritop and Gridtop. The Hextop uses hexagonal pattern, Randtop uses random pattern, Tritop uses triangle pattern and Gridtop uses rectangular grid pattern in the topology of the SOM. For each topology pattern structure, the present paper evaluates the performance of the proposed approach with various neighborhood sizes ranging from 3 to 20. For each experiment of SOM, the distance between the neurons is computed with four different distance measures viz., link dist, man dist, dist and box dist. The dist computes the Euclidean distance, the man dist computes the manhattan distance, the link dist computes the number of links as distance and the box list computes the layer neuron position vector based distance.

For each experiment, the described feature vector is given to the designed SOM with the associated topology structure, neighborhood size and distance function. The performance of the experiment is indicated with fur measures viz., FNR (False Negative Ratio), FPR (false Positive Ratio), TPR (True Positive Ratio) and TNR (True Negative Ratio).

The SOM with Hextop topology structure is considered for the evaluation and the evaluated performance measures are shown in Fig. 4, 8, 12 and 16. The SOM with Randtop topology is considered for the evaluation and the performance measures are shown in Fig. 5, 9, 13 and 17. The SOM with Tritop topology is considered for the evaluation and the performance measures are shown in Fig. 6, 10, 14 and 18. The SOM with Gridtop topology is considered for the evaluation

and the performance measures are shown in Fig. 7, 11, 15 and 19.

For each topology, the FNR is computed with all the four distance measures and are shown in Fig. 4, 5, 6 and 7. In these figures, FNR at various neighborhood sizes are portrayed. From this, it is observed that the least FNR is obtained with Hextop topology. For each topology, the FPR is computed with all the four distance measures and arures shown in Fig. 8, 9, 10 and 11. In these figures, FPR at various neighborhood sizes are portrayed. From this, it is observed that the least FPR is obtained with Randtop topology. For each topology, the TPR is computed with all the four distance measures and are showures in Fig. 12, 13, 14 and 15. In these figures, TPR at various neighborhood sizes are portrayed. From this, it is observed that the highest TPR is obtained with Randtop topology. For each topology, the TNR is computed with all the four distance measures and are shown in Fig. 16, 17, 18 and 19. In these figures, TNR at various neighborhood sizes are portrayed. From this, it is observed that the highest TNR is obtained with Hextop topology.
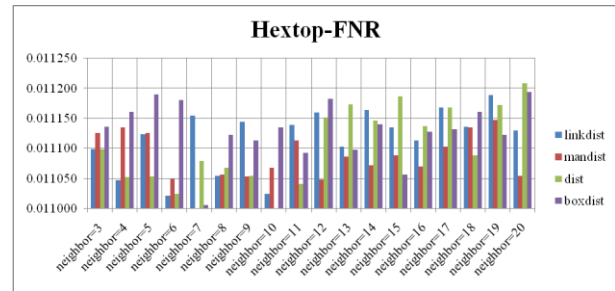

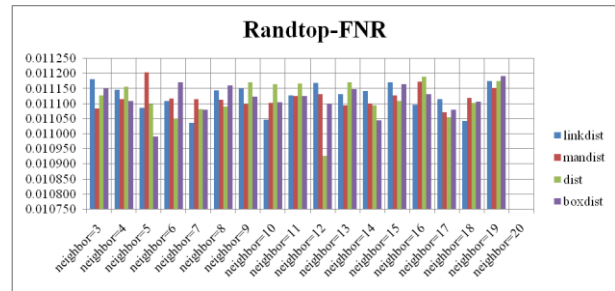Fig. 4. FNR Comparison Result of SOM-Hextop with various distance measures.

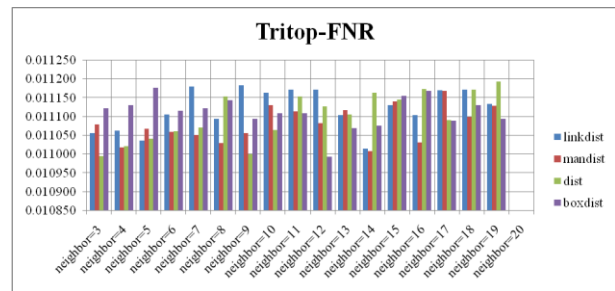Fig. 5. FNR Comparison Result of SOM-Randtop with various distance measures.

Fig. 6. FNR Comparison Result of SOM-Tritop with various distance measures.

Fig. 7. FNR Comparison Result of SOM-Gridtop with various distance measures.

Fig. 8. FPR Comparison Result of SOM-Hextop with various distance measures.

Fig. 9. FPR Comparison Result of SOM-Randtop with various distance measures.

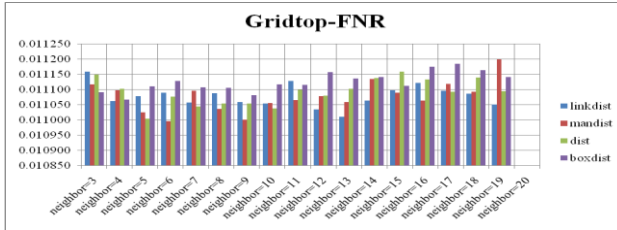Fig. 10. FPR Comparison Result of SOM-Tritop with various distance measures.

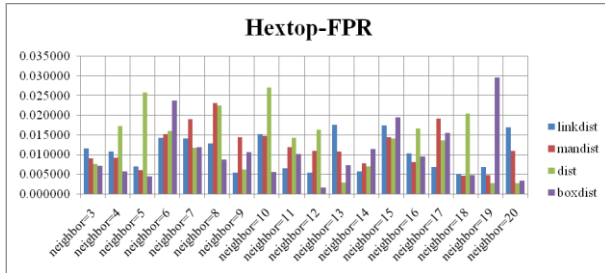Fig. 11. FPR Comparison Result of SOM-Gridtop with various distance measures.

Fig. 12. TPR Comparison Result of SOM-Hextop with various distance measures.
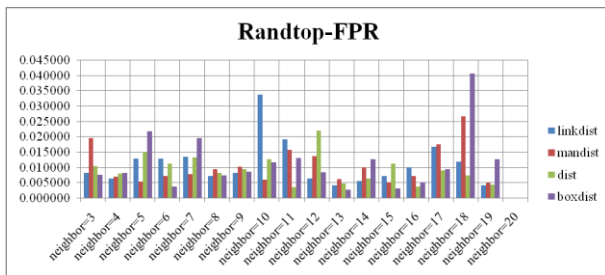

Fig. 13. TPR Comparison Result of SOM-Randtop with various distance measures.

Fig. 14. TPR Comparison Result of SOM-Tritop with various distance measures.

Fig. 15. TPR Comparison Result of SOM-Gridtop with various distance measures.

Fig. 16. TNR Comparison Result of SOM-Hextop with various distance measures.

Fig. 17. TNR Comparison Result of SOM-Randtop with various distance measures.
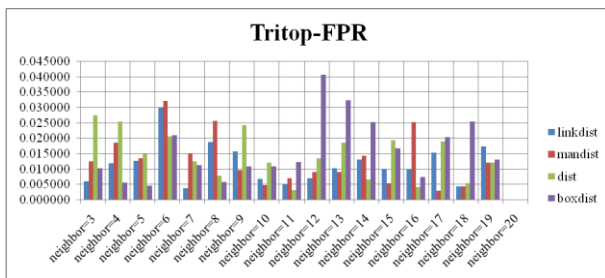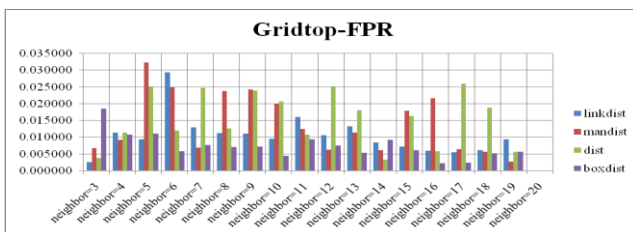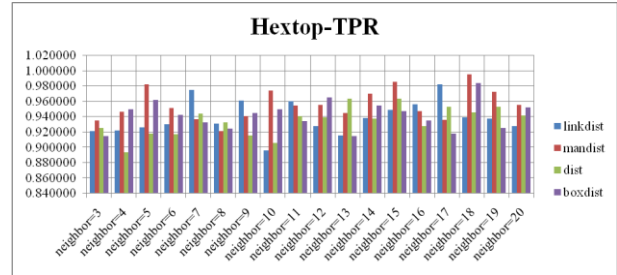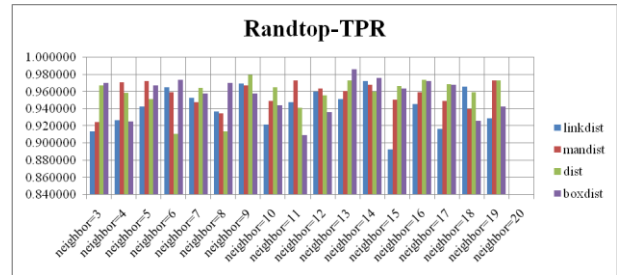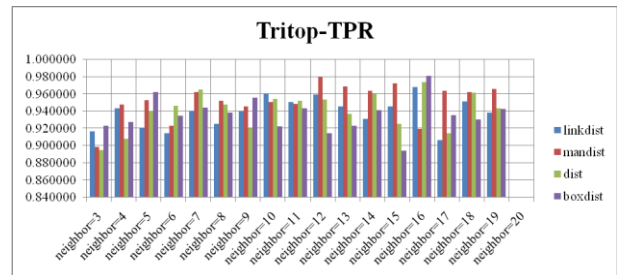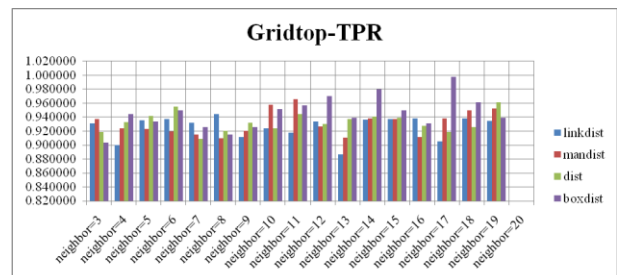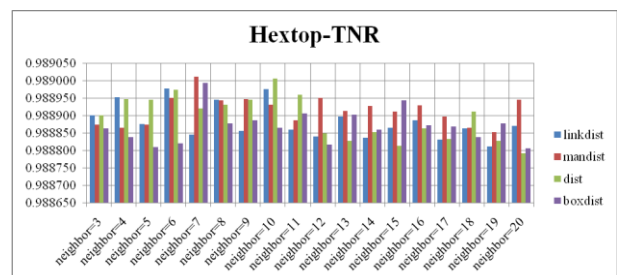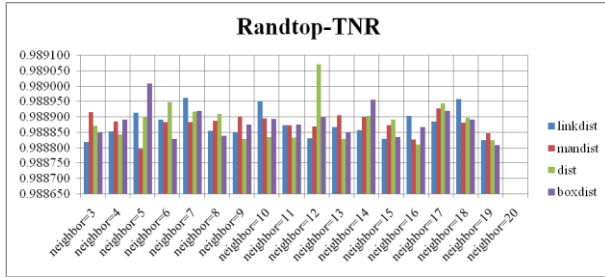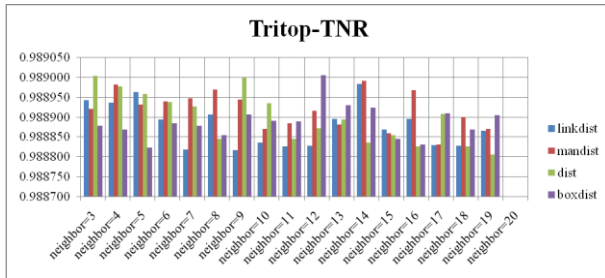

Fig. 18. TNR Comparison Result of SOM-Tritop with various distance measures.

Fig. 19. TNR Comparison Result of SOM-Gridtop with various distance measures.

Fig. 20. FNR Comparison Result of SOM-Box distance measure with various topology functions.

Fig. 21. FNR Comparison Result of SOM-Link distance measure with various topology functions.

Fig. 22. FNR Comparison Result of SOM-Man distance measure with various topology functions.

Fig. 23. FNR Comparison Result of SOM-dist distance measure with various topology functions.

Fig. 24. FPR Comparison Result of SOM-Box distance measure with various topology functions.

Fig. 25. FPR Comparison Result of SOM-Link distance measure with various topology functions.

The FNR measure with Boxdist distance function is shown in Fig. 20. The least FNR value is obtained at neighborhood (NH)=4 with Randtop and NH=10 with Tritop. The FNR measure with Linkdist distance function is shown in Fig. 21. The least FNR value is obtained at NH=13 with Gridtop and NH=14 with Tritop. The FNR measure with Mandist distance function is shown in Fig. 22. The least FNR value is obtained at NH=7 with Hextop. The FNR measure with dist distance function is shown in Fig. 23. The least FNR value is obtained at NH=12 with Randtop.

The FPR measure with Boxdist distance function is shown in Fig. 24. The least FPR value is obtained at NH=12 to 16 with Hextop, Randtop and Gridtop. The FPR measure with Linkdist distance function is shown in Fig. 25. The least FPR value is obtained at NH=3 with Gridtop. The FPR measure with Mandist distance function is shown in Fig. 26. The least FPR value is obtained at NH=18 with Tritop and NH=19 with Gridtop. The FPR measure with dist distance function is shown in Fig. 27. The least FPR value is obtained at NH=19, 20 with Hextop.

Fig. 26. FPR Comparison Result of SOM-Man distance measure with various topology functions.

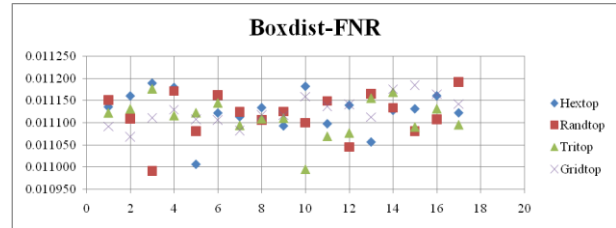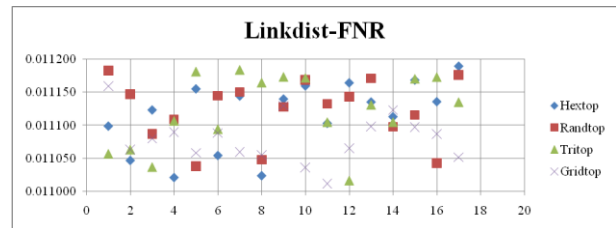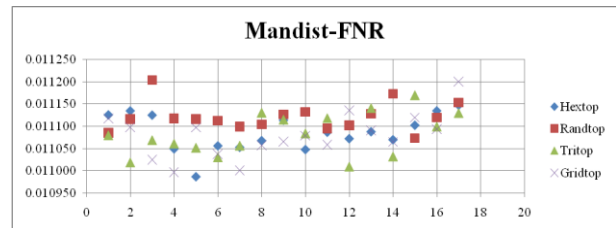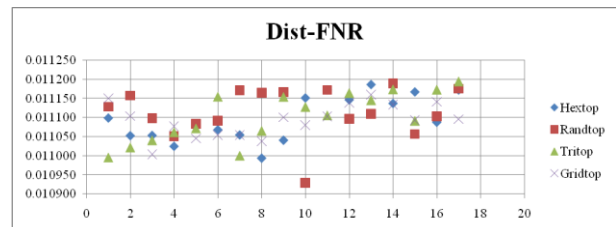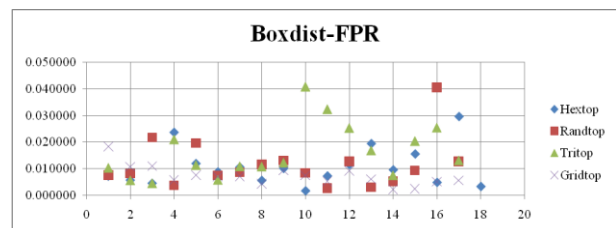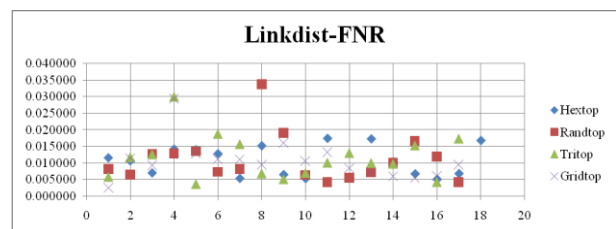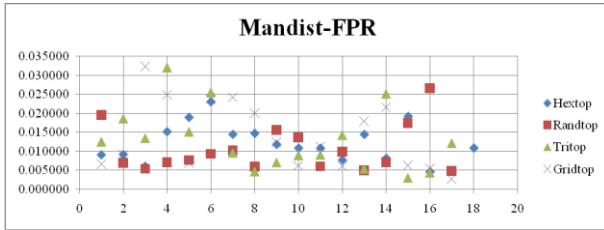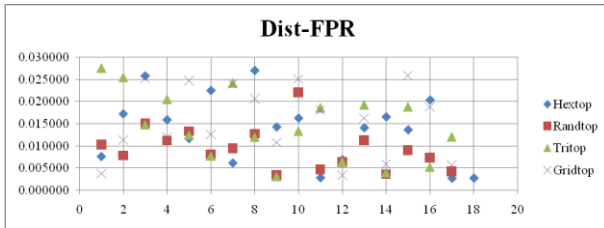Fig. 27. FPR Comparison Result of SOM-dist distance measure with various topology functions.

The present paper extended the present approach with the normalization (norm) process. This will normalizes the derived feature vector to a length of 1 and the normalized result is given to the SOM with various topology structures, distance functions. The proposed approach is extended with various probability distribution functions (PDFs). For this, the present paper uses the following PDFs.

- Poisson PDF (poisPDF)
- Exponential PDF (expPDF)
- Extreme Value PDF (evpPDF)
- Weibel PDF (wblPDF)
- Chi Square PDF (chi2PDF)

These results are evaluated with SOM neighborhood size=3. The SOM with Hextop structure is used for the evaluation and the performance measures with various distance measures are shown in Tables 1, 2, 3 and 4. From these results, it is observed that for SOM with Hextop structure, efficient results are obtained by evpPDF for linkdist distance measure, poisPDF for man dist distance measure, evpPDF for dist distance measure and poisPDF for box dist distance measure. The SOM with Randtop structure is used for the evaluation and the performance measures with various distance measures are shown in Tables 5, 6, 7 and 8. From these results, it is observed that for SOM with Randtop structure, efficient results are obtained by original (org) for linkdist distance measure, chi2PDF for man dist distance measure, norm for dist distance measure and evpPDF for box dist distance measure. The SOM with Tritop structure is used for the evaluation and the performance measures with various distance measures are shown in Tables 9, 10, 11 and 12. From these results, it is observed that for SOM with Tritop structure, efficient results are obtained by chi2PDF for linkdist distance measure, evpPDF for man

dist distance measure, chi2PDF for dist distance measure and chi2PDF for box dist distance measure. The SOM with Gridtop structure is used for the evaluation and the performance measures with various distance measures are shown in Tables 13, 14, 15 and 16. From these results, it is observed that for SOM with Gridtop structure, efficient results are obtained by evpPDF for linkdist distance measure, chi2PDF for man dist distance measure, evpPDF for dist distance measure and chi2PDF for box dist distance measure.

Table.1 Hextop-linkdist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011099	0.011622	0.921712	0.988901
norm	0.011090	0.009224	0.857443	0.988910
poisPDF	0.011221	0.000463	0.488426	0.988779
expPDF	0.011173	0.004571	0.773207	0.988827
evpPDF	0.011096	0.008717	0.969061	0.988904
wblPDF	0.011159	0.002972	0.797028	0.988841
chi2PDF	0.011156	0.006868	0.970909	0.988844

Table.2 Hextop-man dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011126	0.009069	0.935376	0.988874
norm	0.011049	0.020867	0.901355	0.988951
poisPDF	0.011194	0.001667	0.931667	0.988806
expPDF	0.011181	0.000859	0.854697	0.988819
evpPDF	0.011151	0.004452	0.984437	0.988849
wblPDF	0.011117	0.013056	0.864722	0.988883
chi2PDF	0.011154	0.010463	0.922870	0.988846

Table.3 Hextop- dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011099	0.007640	0.925693	0.988901
norm	0.011094	0.010172	0.945383	0.988906
poisPDF	0.011141	0.000823	0.921399	0.988859
expPDF	0.011195	0.002448	0.764219	0.988805
evpPDF	0.011053	0.021482	0.956296	0.988947
wblPDF	0.011177	0.002275	0.786614	0.988823
chi2PDF	0.011122	0.007053	0.970725	0.988878

Table.4 Hextop-box dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011136	0.007151	0.915071	0.988864
norm	0.011139	0.004318	0.917904	0.988861
poisPDF	0.011140	0.004769	0.950787	0.988860
expPDF	0.011093	0.004384	0.806727	0.988907
evpPDF	0.011126	0.014597	0.963181	0.988874
wblPDF	0.011078	0.017840	0.837715	0.988922
chi2PDF	0.011175	0.004582	0.984307	0.988825

Table.5 Randtop-linkdist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011129	0.008218	0.980671	0.988871
norm	0.011125	0.007328	0.837116	0.988875
poisPDF	0.011169	0.002677	0.486212	0.988831
expPDF	0.011174	0.001100	0.843344	0.988826
evpPDF	0.011132	0.013776	0.975113	0.988868
wblPDF	0.011108	0.009069	0.757597	0.988892
chi2PDF	0.011146	0.006351	0.971427	0.988854

Table.6 Randtop-man dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011183	0.008182	0.958485	0.988817
norm	0.011032	0.013431	0.975458	0.988968
poisPDF	0.011161	0.005278	0.661389	0.988839
expPDF	0.011162	0.000513	0.855043	0.988838
evpPDF	0.011023	0.017981	0.948686	0.988977
wblPDF	0.011198	0.002698	0.819524	0.988802
chi2PDF	0.011142	0.004082	0.973696	0.988858

Table.7 Randtop- dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011034	0.016052	0.950615	0.988966
norm	0.011070	0.008711	0.957956	0.988930
poisPDF	0.011133	0.004264	0.473514	0.988867
expPDF	0.011116	0.002873	0.841571	0.988884
evpPDF	0.011117	0.015200	0.940355	0.988883
wblPDF	0.011097	0.005831	0.838613	0.988903
chi2PDF	0.011060	0.014216	0.985784	0.988940

Table.8 Randtop-box dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011068	0.011504	0.955163	0.988932
norm	0.011127	0.006955	0.948600	0.988873
poisPDF	0.011125	0.004071	0.618152	0.988875
expPDF	0.011084	0.003421	0.818801	0.988916
evpPDF	0.011081	0.008237	0.991763	0.988919
wblPDF	0.011152	0.008770	0.813452	0.988848
chi2PDF	0.011192	0.001202	0.976576	0.988808

Table.9 Tritop-linkdist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011125	0.007852	0.958815	0.988875
norm	0.011140	0.007000	0.804111	0.988860
poisPDF	0.011105	0.005925	0.538520	0.988895
expPDF	0.011119	0.007823	0.747733	0.988881
evpPDF	0.011051	0.021112	0.967777	0.988949
wblPDF	0.011136	0.005208	0.794792	0.988864
chi2PDF	0.011231	0.001238	0.976539	0.988769

Table.10 Tritop-man dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011171	0.006931	0.948624	0.988829
norm	0.011040	0.012365	0.932079	0.988960
poisPDF	0.011134	0.006543	0.549012	0.988866
expPDF	0.011201	0.000556	0.877222	0.988799
evpPDF	0.011140	0.006906	0.981982	0.988860
wblPDF	0.011161	0.004466	0.895534	0.988839
chi2PDF	0.011169	0.009286	0.912937	0.988831

Table.11 Tritop- dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011081	0.010362	0.911860	0.988919
norm	0.011152	0.003747	0.907364	0.988848
poisPDF	0.011129	0.003589	0.518633	0.988871
expPDF	0.011083	0.003586	0.829747	0.988917
evpPDF	0.011055	0.026878	0.950899	0.988945
wblPDF	0.011160	0.005228	0.750328	0.988840
chi2PDF	0.011141	0.007279	0.959388	0.988859

Table.12 Tritop-box dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011074	0.011142	0.933302	0.988926
norm	0.011145	0.005568	0.905543	0.988855
poisPDF	0.011133	0.003396	0.529938	0.988867
expPDF	0.011061	0.010848	0.811374	0.988939
evpPDF	0.011098	0.010023	0.967755	0.988902
wblPDF	0.011088	0.004139	0.818083	0.988912
chi2PDF	0.011190	0.004074	0.984815	0.988810

Table.13 Gridtop-linkdist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011194	0.003035	0.952521	0.988806
norm	0.011070	0.012077	0.832367	0.988930
poisPDF	0.011105	0.005925	0.538520	0.988895
expPDF	0.011166	0.016914	0.827531	0.988834
evpPDF	0.011171	0.002690	0.975088	0.988829
wblPDF	0.011077	0.016495	0.861282	0.988923
chi2PDF	0.011120	0.019133	0.958645	0.988880

Table.14 Gridtop-man dist with neighborhood=3

	FNR	FPR	TPR	TNR
org	0.011137	0.007817	0.925516	0.988863
norm	0.011097	0.007507	0.881382	0.988903
poisPDF	0.011134	0.006543	0.549012	0.988866
expPDF	0.011192	0.001840	0.831494	0.988808
evpPDF	0.011061	0.012548	0.976341	0.988939
wblPDF	0.011171	0.003884	0.829449	0.988829
chi2PDF	0.011152	0.006815	0.982074	0.988848

Table.15 Gridtop- dist with neighborhood=3

	FNR	*FPR*	*TPR*	*TNR*
org	0.011161	0.006691	0.937754	0.988839
norm	0.011056	0.010466	0.845089	0.988944
poisPDF	0.011129	0.003589	0.518633	0.988871
expPDF	0.011162	0.016874	0.783126	0.988838
evpPDF	0.011152	0.004088	0.984801	0.988848
wblPDF	0.011183	0.011806	0.832639	0.988817
chi2PDF	0.011170	0.006667	0.960000	0.988830

Table.16 Gridtop-box dist with neighborhood=3

	FNR	*FPR*	*TPR*	*TNR*
org	0.011143	0.007129	0.926204	0.988857
norm	0.011148	0.003654	0.796346	0.988852
poisPDF	0.011133	0.003396	0.529938	0.988867
expPDF	0.011055	0.003738	0.774040	0.988945
evpPDF	0.011003	0.024876	0.952902	0.988997
wblPDF	0.011010	0.023719	0.765170	0.988990
chi2PDF	0.011123	0.007302	0.970476	0.988877

V. Conclusion

The present paper proposes an approach for describing the object with spherical contact distribution function. The described features are further represented with normalization and various Probability Distribution Functions (PDFs). Further the represented features are clustered with the Self-Organizing Map (SOM). Experiments are conducted with various topology structures and distance measures. The results show the efficiency of the proposed approach.

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Authors' Profiles

Chamundeswari G. completed her M.Tech from Narasaraopeta College of Engineering during 2007-2009. She registered for Ph.D in JNTUK, Kakinada in 2010. She worked as Assistant Professor in Vegesna Suryanarayana Raju (VSR) Institute of Computer Science, Eluru from 2001 to 2009. Then she worked as Assistant Professor in Helapuri Institute of Technology and Science, Eluru from 2009 to 2010. She worked as Associate Professor in Ramachandra College of Engineering, Eluru. She published six papers in various national and international journals and conferences. Her research interests include computer vision, pattern recognition and clustering techniques.

Dr. G. P. Saradhi Varma did his B.E. (CSE) from Manipal Institute of Technology Mangalore University, M.Tech from NIT (REC Warangal), Warangal and Ph.D (Specialized in Computer Science) from Andhra University, Visakhapatnam. He is presently Professor and Principal, SRKR Engineering College, Bhimavaram. He is an Educational member and consultant to various companies and Institutions in Andhra Pradesh. He has a total of 24 research publications at International/National Journals and Conferences. is areas of interest include Object Oriented Technologies, Information Retrieval, Algorithms, Computer Networks, Image Processing.

Dr. Ch. Satyanarayana is a Professor in Computer science and Engineering Department at Jawaharlal Nehru Technological University Kakinada, Kakinada. Currently he is Director Academics and Planning, JNTUK, Kakinada. He has 13 years of experience. His area of interest is on Image processing, Database Management Systems, Speech Recognition, Pattern recognition and network security. He published more than 30 research papers in international journals. He published more than 30 research papers in international conferences.

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