Imperial Journal of Interdisciplinary Research (IJIR)
Vol-2, Issue-7, 2016
ISSN: 2454-1362, http://www.onlinejournal.in

A Literature Survey on Similarity and Dissimilarity of Digital Images

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Abstract: *Segmentation of the image is an important step in image analysis, but it is remains a complex problem. Many segmentation methods have been proposed in the literature but it is difficult to compare their efficiency. In this literature survey we attempt to find the similarity between images by natural segmentation of images into several regions. The research work is based on fuzzy C mean and Delaunay triangulation for image segmentation.*

Index Terms: *Clustering, Probabilistic Clustering, Scalability, Delaunay Graph, Fuzzy C Means, Joint Entropy, Rank Distance.*

1. Introduction

Quantifies the dependency and the independency is measures by the similarity and dissimilarity measures of the images. [63]
Suppose the two 2D images are A and B. Here A=a1,a2,a3….an and B=b1,b2,b3……bn (a1,a2,a3……an and b1,b2,b3……bn are represent intensities of corresponding image pixels respectively). Suppose S is representing the similarity matrix of an image.
S is following that ……

1. Limited Range: $S(X, Y) \leq S_0$, for some arbitrarily large number S_0.
2. Reflexivity: $S(X, Y) = S_0$ if and only if $X = Y$.
3. Symmetry: $S(X, Y) = S(Y,X)$.
4. Triangle Inequality: $S(X, Y)\ S(Y, Z) \leq [Z(X, Y) +S(Y, Z)]\ S(X, Z)$.

S_0 is the largest similarity measure between X and Y images.

Similarity of Images:

There are many techniques to measures the similarity of images. Some of the techniques ar as follows-

Pearson Correlation Coefficient:
It is efficient to measures the similarity of the images. It requires a small number of additions and multiplication of each pixel. So it's computational complexity for images where the size n pixels are on the order n. If correlation coefficient is to be used to locate a template in an image, and if N sub images or windows exist in the image that can be compared to the template, the time required to locate the template inside the image will be proportional to Nn when N and n are large the computation time can be considerable.

Tanimoto Measure:
Tanimoto measure uses the raw intensities. It has been used to measures the similar results of correlation and coefficient. The Tanimoto measure match the template to windows in the image for shown the similarity of image. It's encircled the point of highest similarity, which shows the best result of the similarity measurement in the image.

Stochastic Sign Change:
To finding the simpler number of zero-crossings in the difference image used these measures. Determination of the similarity between two images requires a few additions and comparisons at each pixel. So the computational complexity of the measure is on the order of n.

Minimum Ratio:
It has been another efficient similarity measurement technique to find the similarity of images**.**

Spearman's Rho:
A similarity measure relating to the Pearson correlation coefficient is Spearman rank correlation or Spearman's Rho.

Greatest Deviation:
Ties are possible in a digital image. So remove that ties from the image used the Gaussian of a small standard deviation, such as 1 pixel. This will maintain image details.

Correlation Ratio:
Correlation ratio is a similarity measure. It has been quantifies the degree at which Y is a single-valued function of X. It was first proposed by Pearson. To find the correlation ratio between images X and Y, and intensity of X is i, intensities at the corresponding entries in Y are found here.

Energy of Joint Probability Distribution:
The joint probability distribution (JPD) of the images is reflected the relationship between intensities of two images. Each entry of the joint histogram is divided by n, after obtaining the joint histogram of the images. The number of pixels in each image is mapped by the JPD of the images. It can uniquely map intensities in X to intensities in Y, if Single-valued mapping function exists. The JPD of the image will contain a thin density of points, which showing the single-valued mapping function.

Material Similarity:
The thin density converts to a band of points with the help of width of the band depending on the magnitude of the noise. Single-valued curve represent in mapping, If noise is zero-mean. Used smooth the JPD and look for the peak value at each column to reduce the effect of noise.

Rényi Mutual Information:
Rényi mutual information is defined in terms of Rényi entropy, and Rényi entropy of order α of a finite discrete probability distribution {pi: i = 0, . . . , 255} is defined by

$$R_\alpha = \frac{E^i_\alpha + E^j_\alpha}{E^{ij}_\alpha},$$

Where E^i_α is the Rényi entropy of order α of probability distribution pi =_255 j=0 pij for i = 1, . . . , 255, E^j_α is the Rényi entropy of order α of pj=_255 i=0 pij for j = 0. . . 255, and E^{ij}_α is the Rényi entropy of order α of probability distribution {pij: i, j = 0, . . . , 255}.

Tsallis Mutual Information:
Tsallis entropy is used to calculate the mutual information.

F-Information Measures:
The divergence or distance between the joint distribution and the product of the marginal distributions of two images can be used to measure the similarity between the images. The f -information or f –divergence is used to measures similarity of two images that contains mutual information.

Dissimilarity of Images:

A dissimilarity measure [63] D is considered a metric. It contained the dissimilarity value of the images. A metric dissimilarity D satisfies which is the following the sequences of images X and Y:

1. No negativity: D(X, Y) ≥ 0.
2. Reflexivity: D(X, Y) = 0 if and only if X = Y.
3. Symmetry: D(X, Y) = D(Y, X).
4. Triangle Inequality: D(X, Y) +D(Y, Z) ≥ D(X, Z).

Some of the dissimilarity measure techniques are discuss here.

L1 Norm:
It is one of the oldest dissimilarity measures used to compare images **.**The images are A and B obtained by the same sensor and under the same environmental conditions. And if the sensor has been a very high signal to noise ratio, the L1 norm can produce matching results. It has been accurate results which produced by more expensive measures.

Median of Absolute Differences:
To reduce the effect of impulse noise on the calculated dissimilarity measure used median of absolute differences, which instead of the average of absolute differences. The median of absolute differences (MAD) may be used to measure the dissimilarity between two images.

Square L2 Norm:
Square L2 norm, square Euclidean distance, or sum of squared intensity differences of corresponding pixels Compared to L1 norm. It has been emphasizes larger intensity differences between X and Y. It is one of the popular measures in stereo matching. Compared to Pearson correlation coefficient, this measure is more sensitive. So that of reason it was produce proper results than correlation coefficient.

Median of Square Differences:
The robust version of the square L2 norm is the median of square differences (MSD). When images are corrupted with impulse noise, or one image contains occluded regions with respect to the other, by discarding half of the largest square differences, the influence of noise and occupation is reduce.

Normalized Square L2 Norm:
It is the way to make the measure insensitive to image contrast. The standard deviation of the intensities has been dividing in the mean-normalized intensities in each image by. The sum of squared differences of bias and scale normalized intensities in each image is then used to measure the dissimilarity between the images.

Incremental Sign Distance:
Incremental sign distance is a relatively fast measure. It measures when it requires on the order of n comparisons, additions, and subtractions. The measure is suitable for comparing images which are not noisy but may have considerable intensity differences.

Intensity-Ratio Variance:
The ratio of corresponding intensities across the image domain will be a constant when the intensities in one image are a scaled version of intensities in

another image. When two images are taken at different camera, the measurement can be finding the dissimilarity between them.

Intensity-Mapping-Ratio Variance:
This measure combines correlation ratio for measures intensity mapping variance with the help of intensity-ratio variance. It was less sensitive to multiplicative intensity differences between images than other methods like difference in gains of the sensors. Use of mapping-ratio variance rather than ratio variance makes the measure insensitive to differences in sensor characteristics.

Rank Distance:
Rank distance is one of the fastest methods to find the dissimilarity of images as it requires only a subtraction and a sign check at each pixel once ranks of the intensities are determined.

Joint Entropy:
Entropy means the uncertainty in an outcome. Joint entropy represents uncertainty in joint outcomes. The dependency of joint outcomes determines the joint entropy. The higher the dependency between joint outcomes, the lower the uncertainty will be and, thus, the lower the entropy will be.

Exclusive F-Information:
Information exclusively contained in images A and B when observed jointly is known as exclusive f -information. It is related to joint entropy E(X,Y) and mutual information.

2. Literature Survey

Many of the clustering methods are used to find out the number of clusters but before that we need to give the cluster centres. Fuzzy C mean [51] and New Delaunay segmentation method [1] are unsupervised image segmentation method. The Fuzzy C-Means (FCM) clustering algorithm was first introduced by Dunn [61] and later was extended by Bezdek [5]. The algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted within group sum of squared error objective function. New Delaunay segmentation method [1] is based on the Voronoi Diagram [46] (VD).VD is a well-known technique in computational geometry, which generates clusters of intensity values using information from the vertices of the external boundary of Delaunay triangulation [56] (DT).Using this technique it is possible to produce segmented image region. New Delaunay segmentation method was published by Abbas Cheddad, Dzulkifli Mohamad and Azizah Abd Manaf [46]. In the supervised image segmentation method used the K-means algorithm. Zhexue Huang represents a better technique on the paper [1]. For measurement of similarity and the distance introduce a paper [2] by Seung-Seok Choi, Sung-Hyuk Cha andCharles.K. V. MARDIA AND T. J .HAINSWORTH [3] introduce a thresholding method for the image segmentation “Multichannel Texture Analysis Using Localized Spatial Filters” [4] is introduce by ALAN CONRAD BOVIK, MARIANNA CLARK AND WILSON S. GEISLER.A novel graph theoretic approach [5] for data clustering introduce by Zhenyu Wu and Richard Leahy and it also give the idea of the problem of image segmentation. It is a fast algorithm for computing the maximum flows in an undirected graph. JESC [15] is the fully Auto color image segmentation method. The concept of the chromatography [16] is used for the image segmentation in the “Diagnosis of diabetes by image detection of breath using gas-sensitive laps”. Four research groups have contributed to evaluate their own algorithm for [17] segmenting a range image into planar patches. Mean shift algorithm [18] is used a simple nonparametric procedure for estimating density gradients. Generic Obstacle and Lane Detection system [19] describes the stereo vision-based hardware and software architecture to be used on moving vehicles to increment road safety. Fuzzy c means clustering [47] is used of Thematic Mapper [20] (TM) image data. In the first stage is that the image segmented into "coarse" hard clusters. Adaptive fuzzy clustering [21] scheme for image segmentation is the nonstationary in nature of images.“A Pixel Dissimilarity Measure That Is Insensitive to Image Sampling” [22] is proposed a method which is measure of dissimilarity that is provably insensitive to sampling. An unsupervised video segmentation [23] technique consists of two phases one is initial segmentation and second one is temporal tracking similar to a number of existing techniques. A fast hybrid segmentation algorithm [24] was presented which integrates edge and region-based techniques via the watershed detection algorithm. The normalized cut criterion is measures [25] dissimilarity between the different groups as well as the total similarity within the groups. Fully automated model-based image segmentation [26] is introduce two models representing the objects— 1.shape model and 2.border appearance model. Back ground subtraction is lighting insensitive and suitable for real-time applications. They proposed [28] the use of simplified stereo algorithm to perform the segmentation, which requires at least two camera views to be available. The spatial and intensity transformations is represent a general technique that facilitates nonlinear [29] spatial normalization and image realignment. The Visual Seek [30] system is novel in that the user forms the queries by diagramming spatial arrangements of color regions. Each pixel using a model [30] is introduced of how that pixel looks when it is part of different Classes. K-means algorithm is introduced, with the features of spatial constraints that means Gibbs random [9] field model and account for local intensity variation of images. Several similarity measures like metric base, set theory base, decision theory base etc. It is presents some [10] of designs which is compare many similarity measures application. It takes some texture images and face images. This method is compare with some relative features of the images. In low-level segmentation [11] is used FCM [43] clustering algorithm. A very important problem is model-based vision. A unique instance of a geometric primitive is define by a minimal subset is the smallest number of points. A genetic algorithm [12] based on a minimal subset. An adaptive approach for the important image processing problem [13] of image segmentation can be relies on learning from experience improve the segmentation performance. The first closed loop image segmentation system [14] which incorporates a genetic algorithm to adapt the segmentation process. A neural network-based [32] is upright frontal face detection system. The new family of fuzzy similarity [34] indices is generalized GTI. That provides a framework for similarity assessment that gets human similarity judgment. Here studies the properties one is TIM [34] and TIP [34].The edge detection problem [35] is divided into three staged: filtering, detection, and tracing. Introduce a method which detect faces in color images based [43] on the fuzzy theory. It make two fuzzy models [36] based on the skin color and hair color. A similarity measure is based on fuzzy logic [39].This method is dubbed Fuzzy Feature Contrast (FFC) [39] and is an extension to a more general domain of the Feature Contrast model due to Tversky.GA-clustering [38] was used for searching cluster centres which get the cluster matrix and it is minimized value. In this method shows the GA-clustering [38] algorithm provides a performance that is significantly superior to that of the K-means algorithm [1], a very widely used clustering technique. Fusion of Rough Set Theoretic Approximations [39] is presents FCM [41] [42] color image segmentation algorithm. The goal of this technique is to segment natural images with regions having gradual variations in color value. The method is proposed to use ordinal measure of 35 DCT [40] coefficients of an 8_8 sub-image, and obtained promising test results that were robust to various modifications in this method. The DCT [40] domain scheme made it possible to use a rank matrix of size 35, which is compared to that of size 64 in the spatial domain. Merging the idea of image blocks are artificial neural networks [41] for pixel level multi focus image fusion. Two neural network [7] models are used here the PNN and RBFN [41] respectively. The FCM [48] program is applicable to a wide variety of geostatistical data analysis problems. To overcome the noise sensitiveness of conventional fuzzy c-means (FCM) clustering algorithm [48], a novel extended FCM algorithm for image segmentation is presented in this paper [54].Segmentation of human faces from still images [47] is a research field of rapidly increasing interest. Face location and extraction must first be performed to obtain the approximate, if not exact, representation of a given face in an image. The proposed approach is based on the Voronoi Diagram (VD) [49],a well-known technique in computational geometry, which generates clusters of intensity values using information from the vertices of the external boundary of Delaunay triangulation(DT) [43] .A Distance Transformations [59] applied to segment face features. Given an image or an image Delaunay Triangulation diagram representation [57], the purpose of this project is to identify a near-duplicate in an image database. Segmentation maps act as spatial [50] hypotheses highlighting distinct parts of objects as a whole. This paper investigates segmentation-based image [51] descriptors for object category recognition. An efficient [60] way of dealing with this new development is to develop browsing tools that distill multimedia data as information oriented summaries.[44] It represent a technique by which we can automatically gather the frames of interest in a video for purposes of summarization. They proposed a technique [44] is based on using Delaunay Triangulation for clustering the frames in videos. They represent the frame contents as multi-dimensional point data and use Delaunay Triangulation [46] for clustering them. In contrast to many of the other clustering techniques, the Delaunay clustering algorithm [44] is fully automatic with no user specified parameters and is well suited for batch processing.

3. Popular Clustering Algorithms

K-means: It is one of the simplest unsupervised learning algorithms [64] that solve the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters fixed a priori. The main idea is to define k cancroids, one for each cluster.

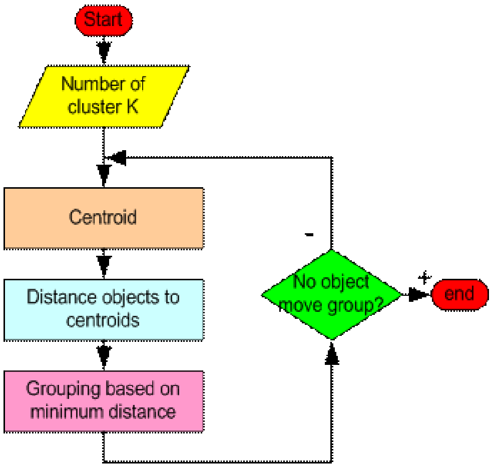


Figure 1: Flow Chart of k-means Algorithm

Algorithm:

Step1: Begin with a decision on the value of k = number of clusters.

Step 2: Put any initial partition that classifies the data into k clusters. You may assign the training samples randomly, or systematically as the following:

a) Take the first k training sample as single-element clusters.

b) Assign each of the remaining (N-k) training sample to the cluster with the nearest centroid. After each assignment, recomputed the centroid of the gaining cluster.

Step 3: Take each sample in sequence and compute its distance from the centroid of each of the clusters. If a sample is not currently in the cluster with the closest centroid, switch this sample to that cluster and update the centroid of the cluster gaining the new sample and the cluster losing the sample.

Step 4: Repeat step 3 until convergence is achieved, that is until a pass through the training sample causes no new assignments.

Fuzzy C-means: Fuzzy c-means (FCM) is a method [7], [11], [17] of clustering which allows one piece of data to belong to two or more clusters.

It is frequently used in pattern recognition. It is based on minimization of the following objective function:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \left\| x_i - c_j \right\|^2 \quad , \quad 1 \le m < \infty$$

Where, m is the real number greater than 1.

u_{ij} is the degree of membership of x_i in the cluster j ,

x_i is the *i*th of d-dimensional measured data, c_j is the d-dimension centre of the cluster, and ||*|| is any norm expressing the similarity between any measured data and the centre.

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership u_{ij} and the cluster centres c_j by

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|}\right)^{\frac{2}{m-1}}}$$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

This iteration will stop when $\max_{ij}\left\{\left|u_{ij}^{(k+1)} - u_{ij}^{(k)}\right|\right\} < \varepsilon$, where ε is a termination criterion between 0 and 1, whereas *k* are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m.

Algorithm:

Step1. Initialize U= [u_{ij}] matrix, $U^{(0)}$

Step2. At k-step: calculate the centres vectors $C^{(k)}=[c_j]$ with $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

Step3.Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|}\right)^{\frac{2}{m-1}}}$$

Step4. If || $U^{(k+1)}$ - $U^{(k)}$||< ε then STOP; otherwise return to step 2.

Hierarchical Clustering: It is a method of cluster analysis [64] which seeks to build a hierarchy of clusters. Use distance matrix as clustering criteria. This method does not require the number of clusters k as an input, but needs a termination condition. Strategies for hierarchical clustering generally fall into two types:

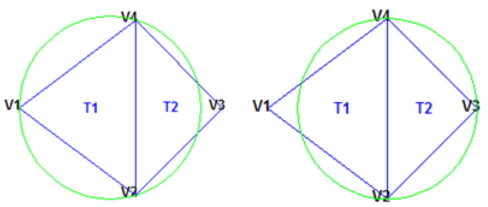
Agglomerative: This is a "bottom up" approach. Termination condition can be specified by the user, as the desired number of clusters. Produces tree of clusters (nodes).

Divisive: This is a "top down" approach. Inverse order of Agglomerative. Decompose data objects into several levels of nested partitioning (tree of clusters), called a dendrogram. A clustering of the data objects is obtained by cutting the dendrogram at the desired level. Then each connected component forms a cluster.

Mixture of Gaussians: The most widely used clustering method of this kind is the one based on learning a mixture of Gaussian [64].

Delaunay Triangulation: It is follows the empty circle property. Empty circle has o vertex. Delaunay triangulation [43],[44] is that which have outer polygon must be convexhull and internal faces must be triangle, which could not be triangulated further. Choose those triangles which are not longer and skinny.

The fundamental property is the Delaunay criterion. In the [56], [57] case of 2-D triangulations, this is often called the empty circumcircle criterion. For a set of points in 2-D, a Delaunay triangulation of these points ensures the circumcircle associated with each triangle contains no other point in its interior. This property is important. In the illustration below, the circumcircle associated with T1 is empty. It does not contain a point in its interior. The circumcircle associated with T2 is empty. It does not contain a point in its interior. This triangulation is a Delaunay triangulation.



Delaunay graph: Delaunay Graph [65] of a set of points P is the dual graph of the Voronoi diagram of P. The Voronoi diagram Vor(P) is the subdivision of the plane into Voronoi cells V(p) for all $p \in P$.

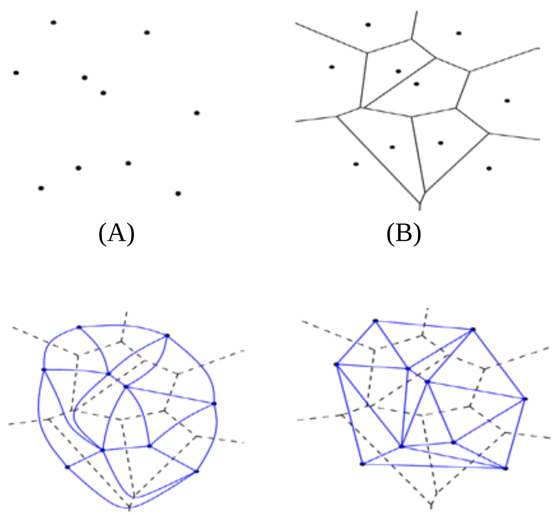


Figure 2: (A) Here P be the set and it has n number of point in the plane, (B) This figure is detonated it is a voronoi diagram and it subdivided of the plane into voronoi cells, (C) This one is the dual graph of voronoi diagram, (D) This is the Delaunay graph which is embedding straight line of dual graph.

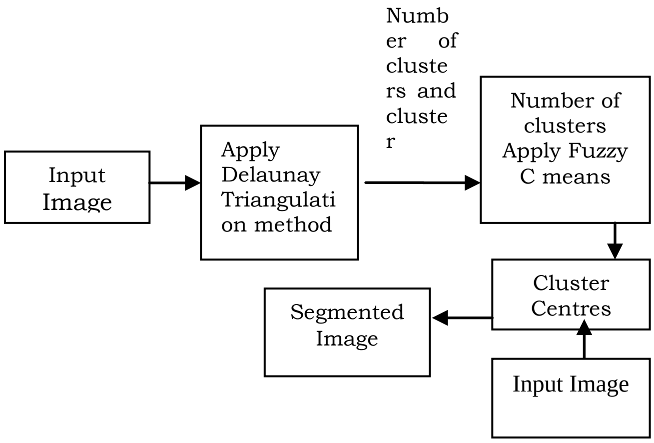


Figure 2: Flow chart of Delaunay Triangulation

The different steps [1][43][46] are described in below:

1. Take an Image as Input Image.
2. Then apply the Delaunay Triangulation method on that image. The Delaunay Triangulation method finds the number of clusters and cluster centres. Then the method was take a decision and further prosed with the value of Number of clusters.
3. The Number of clusters was applying in Fuzzy C Means and get the Cluster centres.
4. The cluster centres apply on the image.
5. After that image is segmented.

4. Conclusion and Future Work

Through this literature survey of popular algorithms, we found several alternative image segmentation methods, which are very efficient to generate number of clusters and cluster centres. This methods are not so fast and useful for both unsupervised and supervised images. Finding out the number of cluster centers is not so easy. The object boundaries are not always well segmented. To find the cluster centres it requires good segmentation of the image. These algorithms are only applicable on the images. The future work will be done towards designing an algorithm which will be implemented on different videos, for detecting similarity and Dissimilarity.

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