ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 4, April 2017

A Review on Image Compression Techniques using K- Means and EM Algorithms

Baddepaka Prasad[1],Andugula Bharath[2],Palla Pavankumar[3]

[1] Assistant Professor, Department of CSE, Keshav Memorial Institute of Technology, Narayanaguda, Telangana, India
[2] Assistant Professor, Department of CSE, Guru nanak Institute of Technology, Hyderabad, Telangana, India
[3] Assistant Professor, Department of CSE, Keshav Memorial Institute of Technology, Narayanaguda,Telangana, India

ABSTRACT*:* In image analysis, segmentation is the partitioning of a digital image into multiple regions (sets of pixels), according to some homogeneity criterion. The problem of segmentation is a well-studied one in literature and there are a wide variety of approaches that are used. Different approaches are suited to different types of images and the quality of output of a particular algorithm is difficult to measure quantitatively due to the fact that there may be much "correct" segmentation for a single image. Here we analyse two unsupervised learning algorithms namely the K-means and EM and compare it with a graph based algorithm, the Normalized Cut algorithm. The K-Means and EM (Expectation Maximization) are clustering algorithms, which partition a data set into clusters according to some defined distance measure. The Normalized Cut criterion takes a measure of the similarity between data elements of a group and the dissimilarity between different groups for segmenting the images.

KEYWORDS: Image analysis, Segmentation, Unsupervised Learning, K- Means and EM algorithms, Normalized Cut.

I. INTRODUCTION

Images are considered as one of the most important medium of conveying information. Understanding images and extracting the information from them such that the information can be used for other tasks is an important aspect of Machine learning. An example of the same would be the use of images for navigation of robots. Other applications like extracting malign tissues from body scan etc form integral part of Medical diagnosis. One of the first steps in direction of understanding images is to segment them and find out different objects in them. To do this, features like the histogram plots and the frequency domain transform can be used. In this paper, we look at three algorithms namely K - Means clustering, Expectation Maximization (EM) and the Normalized cuts and compare them for image segmentation. The comparison is based on various error metrics and time complexity of the algorithms. It has been assumed that the number of segments in the image is known and hence can be passed to the algorithm.

Segmentation is the process of partitioning an image into non-intersecting regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous. The goal of segmentation is typically to locate certain objects of interest which may be depicted in the image. Segmentation could therefore be seen as a computer vision problem. A simple example of segmentation is thresholding a greyscale image with a fixed threshold t: each pixel p is assigned to one of two classes, P_0 or P_1, depending on whether $I(p)< t$ or $I(p)>= t$.

For intensity images (i.e., those represented by point-wise intensity levels), four popular segmentation approaches are: threshold techniques, edge- based methods, region-based techniques, and connectivity-preserving relaxation methods.

1.1 Threshold techniques

The decisions based local pixel information and are effective when the intensity levels of the objects fall squarely outside the range of levels in the background. Because spatial information is ignored, however, blurred region boundaries can create havoc.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 4, April 2017

1.2 Edge-based methods

Center around contour detection their weakness in connecting together broken contour lines make them, too, prone to failure in the presence of blurring.

1.3 A region-based method

The image is partitioned into connected regions by grouping neighbouring pixels of similar intensity levels. Adjacent regions are then merged under some criterion involving perhaps homogeneity or sharpness of region boundaries. Over stringent criteria create fragmentation; lenient ones overlook blurred boundaries and over merge.

1.4 A connectivity-preserving relaxation-based

Segmentation method, usually referred to as the *active contour model*, starts with some initial boundary shape represented in the form of spline curves, and iteratively modifies it by applying various shrink/expansion operations according to some energy function. Although the energy-minimizing model is not new, coupling it with the maintenance of an "elastic" contour model gives it an interesting new twist. As usual with such methods, getting trapped into a local minimum is a risk against which one must guard this is no easy task

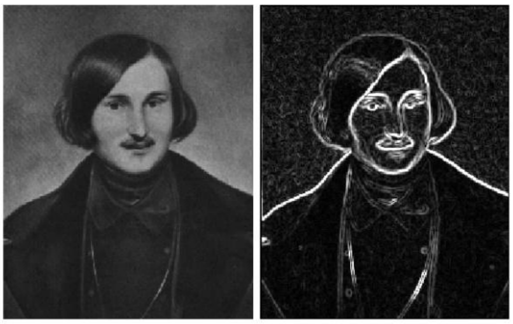
II. RELATED WORK

2.1 Segmentation by Edge Detection

The edge-based methods make use of various edge operators to produce an "edginess" value at each pixel. The values are then thresholded to obtain the edges. The regions within connected edges can be considered as different segments because they lack continuity with adjacent regions. The Sobel operator was studied and implemented to find edges in images[7]. The edges thus found could also be used as aids by other image segmentation algorithms for refinement of segmentation results.

In simple terms, the operator calculates the gradient of the image intensity[2] at each point, giving the direction of the largest possible increase from light to dark and the rate of change in that direction. The result therefore shows how "abruptly" or "smoothly" the image changes at that point and therefore how likely it is that that part of the image represents an edge, as well as how that edge is likely to be oriented. In practice, the magnitude (likelihood of an edge) calculation[5] is more reliable and easier to interpret than the direction calculation.

In theory at least, the operator consists of a pair of 3 X 3 convolution masks as shown in Figure 1. One mask is simply the other rotated by 90 degrees. This is very similar to the Roberts Cross operator[1].



In theory at least, the operator consists of a pair of 3×3 convolution masks as shown in Figure 1. One mask is simply the other rotated by 90 degrees. This is very similar to the Roberts Cross operator. These masks are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one mask for each of the two perpendicular orientations. The masks can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these Gx and Gy). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient. The gradient magnitude is given by

$$|G| = \sqrt{Gx^2 + Gy^2}$$

2.2 Segmentation by Grouping

Image segmentation can be related to perceptual grouping and organization in vision and several key factors, such as similarity, proximity, and good continuation, lead to visual grouping [1]. However, many of the computational issues

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering
(An ISO 3297: 2007 Certified Organization)
Website: www.ijircce.com
Vol. 5, Issue 4, April 2017

of perceptual grouping have remained unresolved. In this report, graph theoretic approach to this problem is adopted, focusing specifically on the case of image segmentation.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Figure 1: Sobel convolution masks

Figure 2: Edge detection of a man's image with the Sobel operator

Figure 3: Edge detection of a clown image with the Sobel operator

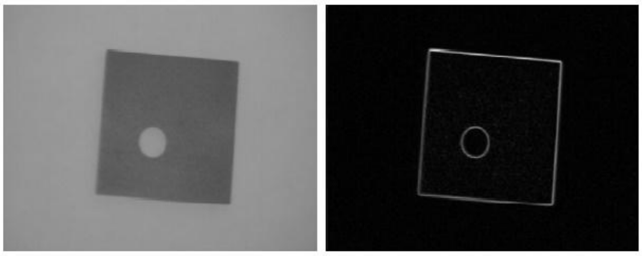


Figure 4: Edge detection of a wedge image with the Sobel operator

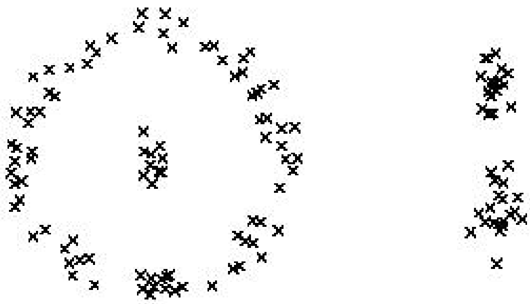


Figure 5: Points in a plane - what is the "correct" grouping?

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 4, April 2017

Since there are many possible partitions of an image into subsets, how do we pick the "right" one? This is illustrated in Figure 5 where there are multiple groupings possible. There are two aspects to be considered here. The first is that there may not be a single correct answer. A Bayesian view is appropriate - there are several possible interpretations in the context of prior world knowledge. The difficulty, of course, is in specifying the prior world knowledge. Some of it is in the form of local properties, such as coherence of brightness, color, texture, or motion, but equally important are global properties about symmetries of objects or object models. The second aspect is that the partitioning is inherently hierarchical. Therefore, it is more appropriate to think of returning a tree structure corresponding to a hierarchical partition instead of a single "flat" partition.

III. IMAGE SEGMENTATION ALGORITHMS

3.1 K-means Clustering Algorithm

K-Means algorithm is an unsupervised clustering algorithm that classifies the input data points into multiple classes based on their inherent distance from each other. The algorithm assumes that the data features form a vector space and tries to find natural clustering in them. The points are clustered around centroids $\mu i \forall i = 1 \ldots k$ which are obtained by minimizing the objective

$$V = \sum_{i=k}^{k} \sum_{xj \in Si} (xj - \mu i) x^2$$

Where there are k clusters Si, i = 1,2….. k and μi is the centroid or mean point of all the points xj ∈ Si As a part of this project, an iterative version of the algorithm was implemented.

The algorithm takes a 2 dimensional image as input. Various steps in the algorithm are as follows:

1. Compute the intensity distribution (also called the histogram) of the intensities.
2. Initialize the centroids with k random intensities.
3. Repeat the following steps until the cluster labels of the image does not change anymore
4. Cluster the points based on distance of their intensities from the centroid intensities

$$C^{(i)} \coloneqq argmin \left\| x^i - \mu_j \right\| x^2$$

5. Compute the new centroid for each of the clusters.

$$\mu_i \coloneqq \frac{\sum_{i=1}^{m} 1\{c_{(i)}=j\} x^{(i)}}{\sum_{i=1}^{m} 1\{C_{(i)}=j\}}$$

Where k is a parameter of the algorithm (the number of clusters to be found), i iterates over the all the intensities, j iterates over all the centroids and μ_i are the centroid intensities.

3.2 EM Algorithm

Expectation Maximization (EM) is one of the most common algorithms used for density estimation of data points in an unsupervised setting. The algorithm relies on finding the maximum likelihood estimates of parameters when the data model depends on certain latent variables. In EM, alternating steps of Expectation (E) and Maximization (M) are performed iteratively till the results converge. The E step computes an expectation of the likelihood by including the latent variables as if they were observed, and maximization (M) step, which computes the maximum

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering
(An ISO 3297: 2007 Certified Organization)
Website: www.ijircce.com
Vol. 5, Issue 4, April 2017

likelihood estimates of the parameters by maximizing the expected likelihood found on the last E step [1]. The parameters found on the M step are then used to begin another E step, and the process is repeated until convergence.

Mathematically for a given training dataset *{x(1), x(i2,……. x(m))}* and model p(**x, z**) where z is the latent variable, We have:

$$\tau(\theta) = \sum_{i=1}^{m} logp(x;\theta)$$

$= \sum_{i=1}^{m} log \sum_{z} p(x, z; \theta)$

As can be seen from the above equation, the log likelihood is described in terms of x, zandθ. But since z, the latent variable is not known; we use approximations in its place.
These approximations take the form of E & M steps mentioned above and formulated mathematically below.

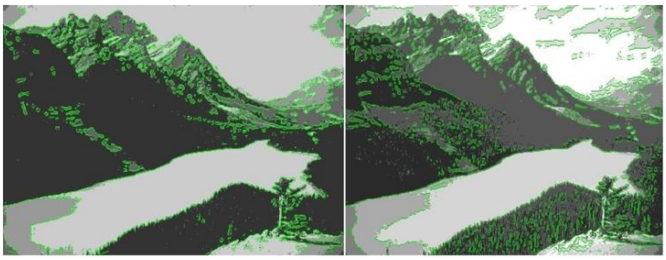
E Step, for each i:

$$Q_i(z^i) \coloneqq p(|z^{(i)}|x^{(i)};\theta)$$

M Step, for all z:

$$\theta{:} = argmax \sum_{i} \sum_{z^{(i)}} Q_i\left(z^{(i)}\right) log \frac{p(x^{(i)}, z^{(i)};\theta)}{Q_i(z^{(i)})}$$

Where Q_i is the *posterior* distribution of $z^{(i)}$'s given the $x^{(i)}$'s



Conceptually, The EM algorithm can be considered as a variant of the K Means algorithm where the membership of any given point to the clusters is not complete and can be fractional

3.3 Normalized Cuts-A graph Partitioning approach

Image segmentation can also be viewed as an optimal partitioning of a graph. The image is presented as a weighted undirected graph G = (V, E). This image graph can be partitioned into two sub graphs A and B by modeling the partition as minimizing the cut as defined below:

$$cut(A, B) = \sum_{u \in A} w(u, v)$$

Where w (i, j) the weight of each edge is a function of the similarity between nodes I and j. However the minimum cut criteria favors cutting small sets of isolated nodes in the graph.To overcome these outliers we can use a modified cost function, Normalized Cut as defined below.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 4, April 2017

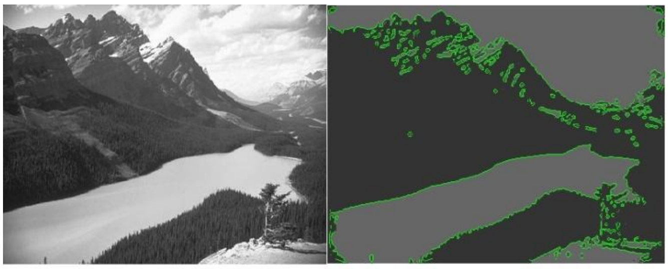
$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)},$$

$$assoc(A,V) = \sum_{u \epsilon A, t \epsilon V} w(u,t)$$

The association value, assoc(A,V), is the total connection from nodes A to all nodes in the graph. Ncut value won't be small for the cut that partitions isolating points, because the cut value will be a large percentage of the total connection from that set to the others.

IV. RESULTS

We applied the partitioning algorithm to gray-scaled images. The segmentation results as generated on different images by each algorithm for varying value of k is as shown in figure
a, b, c, and d.



(a) Original (b) K=2

(c) K=4 (d) K=6

V. CONCLUSION

We implemented the EM and K-means clustering algorithm and used it for intensity segmentation. For smaller values of k the algorithms give good results. For larger values of k, the segmentation is very coarse, many clusters appear in the images at discrete places. This is because Euclidean distance is not a very good metric for segmentation processes.

Better algorithms like the graph based N Cuts give good results for larger value of k. One basic difference between N cuts and clustering algorithms is that clustering algorithms consider pixels with relatively close intensity values as belonging to one segment, even if they are not locationally close. N-cuts considers such areas as separate segments. N Cuts implementation is computationally complex. The eigen value method take a longtime for a full scale image. Images have to be resized to get faster results.We used the authors[1] implementation of N Cuts to visualize the results. Future work includes analyzing other machine learning algorithms like neural networks and SVM for image segmentation.

REFERENCES

[1] Jianbo Shi & Jitendra Malik (1997) Normalized Cuts and Image Segmentation, Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp. 731-737.
[2] T. Kanungo, D. M. Mount, N. Netanyahu, C. Piatko, R. Silverman, & A. Y.Wu (2002) An efficient k-means clustering algorithm: Analysis and implementation Proc. IEEE Conf. Computer Vision and Pattern Recognition, pp.881-892.
[3] D. Arthur, & S. Vassilvitskii (2007) k-mean++ The advantage of Careful Seeding. Symposium of Discrete Algorithms.
[4] M. Wertheimer, "Laws of Organization in Perceptual Forms", A Sourcebook of Gestalt Psychology, W.B. Ellis, ed., pp. 71-88, Harcourt, Brace, 1938.
[5] S. K. Pal and N. R. Pal, "A Review on Image Segmentation Techniques", Pattern Recognition, Vol. 26, No. 9, pp. 1277-1294, 1993.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 4, April 2017

[6] Z. Wu and R. Leahy, "An Optimal Graph Theoretic Approach to Data Clustering: Theory and Its Application to Image Segmentation", IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 15, No. 11, pp. 1101-1113, Nov. 1993.
[7] J. Shi and J. Malik, "Normalized Cuts and Image Segmentation," IEEE Trans. Pattern Analysis and Machine Intelligence, Vol. 22, No. 8, pp. 888-905, Aug. 2000.
[8] R. C. Gonzalez and R. E. Woods. Digital Image Processing, 2nd ed., Pearson Education, 2000.

BIOGRAPHY

Baddepaka Prasad is an Assistant Professor in the Computer Science and Engineering Department, College of Keshav Memorial Institute of Technology, Narayanaguda, Hyderabad. He received Master of Technology (CSE) in 2013 from CVR college of Engg, Hyderabad, India. His research interests are Image Processing, Wireless Sensor Networks, Data mining etc.

Andugula Bharath is an Assistant Professor in the Computer Science and Engineering Department, College of Guru nanak Institiute of Technology, Hyderabad. His research interests are Image Processing, Computer Networks, Data mining etc.

Palla Pavankumar is an Assistant Professor in the Computer Science and Engineering Department, College of Keshav Memorial Institute of Technology, Narayanaguda, Hyderabad. He received Master of Technology (CSE) in 2012 from SKD Engg College, Gooty, Anantapur, India. His research interests are Data mining, Mobile Ad-hoc Networks, Data structures and so on.