Review Article *ISSN: 2319-507X*
Rehana Jamadar, IJPRET, 2013; Volume 1(8): 774-782 *IJPRET*

INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

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REVIEW AND OVERVIEW ON SEGMENTATION OF NOISE CORRUPTED IMAGES

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Accepted Date:

27/02/2013

Publish Date:

01/04/2013

Keywords

Clustering,
Image Segmentation,
Salt-And-Pepper Noise,
Image Processing.

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Abstract

Clustering algorithm is a widely used segmentation method in image processing applications. The algorithm can be easily implemented; however in the occurrence of noise during image acquisition, this might affect the processing results. In order to overcome this drawback, this paper presents a new clustering-based segmentation technique that may be able to find different applications in image segmentation. The proposed algorithm called Denoising-based (DB) clustering algorithm has three variations namely, Denoising-based-K-means (DB-KM), Denoising-based-Fuzzy C-means (DB-FCM), and Denoising-based-Moving K-means (DB-MKM). The proposed DB-clustering algorithms are able to minimize the effects of the Salt-and-Pepper noise during the segmentation process without degrading the fine details of the images. These methods incorporate a noise detection stage to the clustering algorithm, producing an adaptive segmentation technique specifically for segmenting the noisy images.

INTRODUCTION

SEGMENTATION, referring to separating image features from backgrounds, is one of the most important tasks arising from computer vision (e.g., detecting objects) and many image processing fields (e.g., picking out special cells in cell imaging). Image segmentation is the process of dividing digital images into multiple meaningful regions or sets of pixels. Classically, image segmentation is defined as partitioning an image into separate regions which are homogeneous with respect to some characteristics such as gray level or texture. Segmentation methods fall into several categories, including histogram analysis, region growing, edge detection, and partial differential equations (PDE) based variation method. Segmentation algorithms can be classified into different categories based on segmentation techniques used such as the features' thresholding [6], template matching [7], region-based technique [8], [9] and clustering [10], [11]. Those techniques have their own limitations and advantages in terms of suitability, performance and computational cost. For instance, the thresholding technique (providing that the threshold value selected is the suitable one) produces a good quality and rapidity segmentation, but it remains a fact that it is sensitive to noise. Template matching however becomes time-consuming when the image becomes more complex or larger in size while the region-based technique also suffers from time-consuming and over-segmentation problems.

MOTIVATION

2.1 Clustering

The objective of cluster analysis is to partition a given set of objects into homogeneous groups based on given features, such that objects within a group are more similar to each other and more different from objects in other groups [5]. Clustering is an unsupervised classification designed to group a set of data samples with similar characteristics into larger units of analysis (clusters).There exist two categories for clustering tasks: hard and soft clustering. In hard clustering, each data object is assigned to exactly one cluster, while in soft clustering, it is more desirable to let a data object be assigned to several clusters partially. Hence, the soft clustering is also called fuzzy clustering. In image segmentation, clustering algorithm iteratively computes the characteristics of each cluster and segments the image by classifying each pixel in the closest cluster according to a distance metric.

Through clustering technique, a much better results of segmentation can be obtained but over-segmentation is one of the problems that must be faced. Yet, the results of segmentation algorithm (i.e., segmented images) are useful in many ways- it primarily provides easier interpretation of images by highlighting specific objects or features in the image, which serves to be one of the important features in consumer electronics applications.

Pepper & salt noise

Salt & pepper noise is a special case of impulse noise, where a certain percentage of individual pixels in digital image are randomly digitized into two extreme intensities. Normally, these intensities being the maximum and minimum intensities. The contamination of digital image by salt-and-pepper noise is largely caused by error in image acquisition and/or recording. For example, faulty memory locations or impaired pixel sensors can result in digital image being corrupted with salt-and-pepper noise [1]. The need to remove salt-and-pepper noise is imperative before subsequent image processing tasks such as edge detection or segmentation is carried out. This is because the occurrence of salt-and-pepper noise can Severely damage the information or data embedded in the original image. Conventionally, in the occurrence of Salt-and-Pepper noise in images, segmentation can only be applied after performing pre-processing tasks like filtering algorithm. To tackle this problem, we propose new clustering algorithms for segmenting noisy images by incorporating the noise detection stage with the clustering algorithm to introduce an adaptive clustering-based segmentation technique. The adaptive behavior enables the clustering algorithm to segment the noisy image properly even in the occurrence of low density Salt-and-Pepper noise without going through any filtering stage beforehand. The inherited noise detection behavior will improve the segmentation results by only selecting noise-free pixels for the process of segmentation.

CONVENTIONALCLUSTERING ALGORITHMS

Generally, clustering methods can be categorized into historical, graph theoretic, decomposing a density function and minimizing an objective function [21]. In this paper, the focus is on clustering methods by minimizing an objective function and their application for segmenting images.

K-means clustering

K-Means is a simple but well known algorithm for grouping objects, clustering. Again all objects need to be represented as a set of numerical features. In addition the user has to specify the number of groups (referred to as *k*) he wishes to identify. Each object can be thought of as being represented by some feature vector in an *n* dimensional space, *n* being the number of all features used to describe the objects to cluster. The algorithm then randomly chooses *k* points in that vector space, these points serve as the initial centers of the clusters. Afterwards all objects are each assigned to center they are closest to. Usually the distance measure is chosen by the user and determined by the learning task. After that, for each cluster a new center is computed by averaging the feature vectors of all objects assigned to it. The process of assigning objects and recomputing centers is repeated until the process converges. The algorithm can be proven to converge after a finite number of iterations.

Fuzzy c-means

Fuzzy segmentation methods, especially the fuzzy c-means algorithm (FCM)[4], have been widely used in the image segmentation and such a success chiefly attributes to the introduction of fuzziness for the belongingness of each image pixel. This allows for the ability to make the clustering methods able to retain more information from the original image than the crisp or hard segmentation methods [5]. Clustering is used to partition a set of given observed input data vectors or image pixels into clusters so that members of the same cluster are similar to one another than to members of other clusters where the number of clusters is usually predefined or set by some validity criterion or a priori knowledge.

Moving K-Moving (MKM) Clustering The MKM algorithm is the modified version of KM proposed by [14] where the new position for each cluster is calculated using (2). [14] Has introduced the concept of fitness to ensure that each cluster should have a significant number of members and final fitness values before the new position of cluster is calculated. These conventional clustering algorithms especially FCM have been widely used in the image segmentation [12],[13], [15]. [13] in their studies agree that FCM algorithm functions well on most noise-free images, although it fails to segment images which are corrupted by noise. Therefore, in the next section we shall introduce adaptive clustering algorithms employed for the segmentation of noisy images.

The proposed adaptive clustering based segmentation technique

The proposed new version of adaptive clustering-based segmentation technique, particularly for images corrupted with a low level of Salt-and-Pepper noise. The technique, known as Denoising Based (DB) clustering is introduced to overcome the problem of noise sensitivity in the segmentation process and to increase the robustness of the clustering algorithms with respect to noise. The proposed technique is divided into two stages. The first stage involves the detection of Salt-and-Pepper noise's intensity and locations. The second stage will perform the clustering process. The 'noise-free' pixels will be totally considered as the input data and they will give full contribution on the clustering process. Otherwise, for the 'noise' pixels, the fuzzy concept is applied to determine the degree of contributions of these 'noise' pixels on the clustering process. The combination of these features (i.e., the noise detection and the clustering), allows more versatile and powerful methods to achieve a better segmentation especially on noisy images.

Noise Detection

In this stage, the histogram of noisy image will be utilized to estimate the two Salt-and-Pepper noise intensities. The detection stage begins by searching for two peaks of intensities, where according to [16], an image corrupted with the Salt-and-Pepper noise will produce two peaks at the noisy image histogram (i.e., either a positive impulse or a negative impulse). Let us consider an 8-bit gray scale digital image with 256 gray levels in the interval [0, 255]. Generally, a Salt-and-Pepper noise takes on the high-end and low-end intensities. It can either be positive or negative where the intensity value for the positive impulse is near 255 (i.e., appears white known as the salt), and the negative impulse with the intensity value of near 0 (i.e., appears black known as te pepper). These two Salt-and-Pepper noise intensities will be used to identify possible 'noise-pixels' in the image. As in [30], [31], a binary noise mask N(i,j) will be created to mark the location of 'noise-pixels' by using;

$$N(i,j) = 0 \text{ , } X(i,j) = L_{salt} \text{ or } L_{pepper}$$
$$1 \quad \text{otherwise}$$

where X(i,j) is the pixel at the location (i,j) with intensity X,N(i,j)=1 represents the 'noise-free' pixel to be retained in the next clustering stage while N(i,j)=0 represents 'noise' pixels.

II Clustering process

In order to allow more versatile and powerful methods of clustering-based segmentation in noisy images, after the binary noise mask N(i,j) is created, a linearly-fuzzy weighted correction value of 'noise' pixel is obtained using:

$X^{l}(i,j) = [1-F(i,j)].\ X(i,j) + F(i,j)\ .M(i,j)$

where $X^{i}(i,j)$ denotes the corrected 'noise' pixel value, M(i,j)is the median value of the considered pixel and its neighboring pixel in n×n window (i.e., n is an odd number and typically set to 3), and F(i,j) is the fuzzy membership used to weigh the linear relationship between the processing pixel, X(i,j), and the median pixel, M(i,j).

Prior to that, the median of the 'noise' pixels is extracted in a 3x3 window given by

$M(i,j) = \text{median}\ \{X(i+k,j+l)\}$ as k,l €(-1,0,1)

After the median pixel is found, the absolute luminance difference, d(i ,j), is computed by using;

$d(i+k, j+l)= |X(i+k,j+l) - X(i,j)|$ with $(i+k, j+l) \neq (i, j)$

Then the local information of the 'noise' pixels in 3x3 window is calculated by taking the maximum value of the absolute luminance difference given by;

$D(i,j) = \max\ \{ d(i+k, j+l) \}$

The choice of the maximum operator rather than minimum operator is justified in [17]. Next the fuzzy concept is applied to the extracted local information, D(i ,j).The fuzzy membership function is defined by; F(i ,j) whereby for optimal performance, the threshold value T1and T2 are set to 10 and 30 respectively as described in [17]. Then the corrected value of noise pixel is calculated. To increase the robustness of KM clustering towards noise, these corrected values (i.e., for the noise pixels) are used to replace original pixels values during the process of assigning the data to their nearest centre. Then the new position for each cluster is calculated using (2). The term V_t in (2) is substituted by

$V_t = \{ X(i,j)$ if $N(i,j) = 1$

$\{ X^{l}(i,j)$ if $N(i,j) = 0$

By employing this concept in the conventional KM clustering algorithm, the new proposed algorithm is called Denoising-based-K-means (DB-KM). The same concept can also be applied to the conventional FCM and MKM. The modified versions of those techniques are called Denoising-based-Fuzzy C-means (DB-FCM) and Denoising-based-Moving K-means (DB-MKM) respectively.

EXPERIMENTAL RESULTS

The experimental results on several standard real images. There is a total of six algorithms used in this study namely the conventional KM, the conventional FCM, the conventional MKM, the proposed DB-KM, DB-FCM, and DB-MKM. The results of the proposed algorithms (i.e., the DB-clustering algorithms) are compared with the conventional clustering algorithms (i.e., KM, FCM, MKM). In this experiment, i have used images corrupted with the salt-and-pepper noise to test the effectiveness and efficiency of the algorithms.

Qualitative Analysis

I have tried to execute the three proposed clustering algorithms as well as three conventional clustering algorithms on several standard real test images contaminated by different levels of salt-and-pepper noise to investigate the robustness of the algorithms. Five out of those tested images are chosen to enable the visualization of the performance of the proposed algorithms.

CONCLUSION

This paper presents new clustering-based segmentation algorithms named Denoising-based clustering algorithm for adaptive segmentation, i.e., for segmenting noise-corrupted images. The qualitative analyses favor the proposed algorithms as good segmentation algorithms where the segmentation is concerned. The proposed algorithms also produce better results as compared to the conventional algorithms through its inclusion of the noise detection stage in its clustering process. This stage could reduce the effect of noise during the segmentation process. Simulation results show that the proposed algorithms are able to remove low density of salt-and-pepper noise (i.e., up to 50%) during the segmentation process. In addition, the recommended algorithms have also successfully preserved important features on digital images.

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