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Novel Edge Detection Algorithm in Eight Different Directions

[1]CH.Raju [2]D.Nagesh Babu [3]S.Amarnath Babu
[1]M.Tech(SE) Student-10F01D2512, St.Ann's College of Engineering & Technology, Chirala,
[2]Assist.Professor in Department of IT, St.Ann's College of Engineering & Technology, Chirala,
[3]Professor and HOD of Department of IT, St.Ann's College of Engineering &Technology, Chirala,

ABSTRACT

Edge detection is one of the important pre-processing steps in image analysis. Edges characterize boundaries and edge detection is one of the most difficult tasks in image processing hence it is a problem of fundamental importance in image processing. Edges in images are areas with strong intensity contrasts and a jump in intensity from one pixel to the next can create major variation in the picture quality. Edge detection of an image significantly reduces the amount of data and filters out useless information, while preserving the important structural properties in an image. Conventionally, mathematical morphology edge detection methods use single and symmetrical structure elements. But they are difficult to detect complex edge feature, because they are only sensitive to image edge which has the same direction of structure elements. This paper proposed a novel edge detection algorithm based on multi-structure elements morphology of eight different directions. The eight different edge detection results are obtained by using morphological gradient algorithm respectively, and final edge results are obtained by using synthetic weighted method. The experimental results showed that the proposed algorithm is more efficient for edge detection than conventional mathematical morphological edge detection algorithms and differential edge detection operators.

Keywords: *Fragmentation, edge detection, SE, catchment basins and MSE*

1. INTRODUCTION

Image Segmentation is the process of partitioning a digital image into multiple regions [6,7,8]. Actually, partitions are different objects in image which have the same features. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. All of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics. Edge detection is one of the most frequently used techniques in digital image processing [8].Clustering is a process for classifying objects or patterns insuch a way that samples of the same cluster are more similar to one another than samples belonging to different clusters. There are two main clustering strategies: the hard clustering scheme and the fuzzy clustering scheme. The conventional hard clustering methods classify each point of the data set just to one cluster. As a consequence, the results are often very crisp, i.e., in image clustering each pixel of the image belongs just to one cluster. However, in many real situations, issues such as limited spatial resolution, poor contrast, overlapping intensities, noise and intensity in homogeneities reduce the effectiveness of hard (crisp) clustering methods.

Fuzzy C-Means Algorithms:

Fuzzy set theory has introduced the idea of partial membership, described by a membership function. Fuzzy clustering, as a soft segmentation method, has been widely studied and successfully applied in image clustering and segmentation]. Among the fuzzy clustering methods, fuzzy c-means (FCM) algorithm is the most popular method used in image segmentation because it has robust characteristics for ambiguity and can retain much more information than hard segmentation methods Although the conventional FCM algorithm works well on most noise-free images, it is very sensitive to noise and other imaging artifacts, since itdoes not consider any information about spatial context.To compensate this drawback of FCM, a preprocessing image smoothing step has been proposed in and. However,by using smoothing filters important image details can belost, especially boundaries or edges. Moreover, there is no wayto control the trade-off between smoothing and clustering. Thus,many researchers have incorporated local spatial information into the original FCM algorithm to improve the performance of image segmentation.Tolias and Panas developed a fuzzy rule-based scheme called the ruled-based neighborhood enhancement system to impose spatial constraints by postprocessing the FCM clustering results.

Noordam *et al.* proposed a geometrically guided FCM(GG-FCM) algorithm, a semi-supervised FCM technique,where a geometrical condition is used determined by taking into account the local neighborhood of each pixel. Pham modified the FCM objective function by including a spatial penalty on the membership functions. The penalty term leads to an iterative algorithm, which is very similar to the original FCM and allows the estimation of spatially smooth membership functions.

Ahmed *et al.* proposed FCM_S where the objective function of the classical FCM is modified in order to compensate the intensity inhomogeneity and allow the labelling of a pixel to be influenced by the labels in its immediate neighborhood. One disadvantage of FCM_S is

that the neighborhood labelling is computed in each iteration step, something that is very time-consuming.
Chen and Zhang proposed FCM_S1 and FCM_S2, two variants of FCM_S algorithm in order to reduce the computationaltime. These two algorithms introduced the extra mean and median-filtered image, respectively, which can be computed in advance, to replace the neighborhood term of FCM_S. Thus, the execution times of both FCM_S1 and FCM_S2 are considerably reduced. Szilagyi *et al.* proposed the enhanced FCM (EnFCM) algorithm to accelerate the image segmentation process. The structure of the EnFCM is different from that of FCM_S and its variants. First, a linearly-weighted sum image is formed from both original image and each pixel's local neighborhood average gray level. Then clustering is performed on the basis ofthe gray level histogram instead of pixels of the summed image. Since, the number of gray levels in an image is generally much smaller than the number of its pixels, the computational time of EnFCM algorithm is reduced, while the quality of the segmented image is comparable to that of FCM_S.
More recently, Cai *et al.* [16] proposed the fast generalized FCM algorithm (FGFCM) which incorporates the spatial information, the intensity of the local pixel neighborhood and the number of gray levels in an image. This algorithm forms a nonlinearly-weighted sum image from both original image and its local spatial and gray level neighborhood. The computationaltime of FGFCM is very small, since clustering is performed onthe basis of the gray level histogram. The quality of the segmented image is well enhanced However, EnFCM as well as FGFCM, share a common crucial parameter (or). This parameter is used to control the tradeoff between the original image and its corresponding mean or median-filtered image. It has a crucial impact on the performance of those methods, but its selection is generally difficult because it should keep a balance between robustness to noise and effectiveness of preserving the details. In other words, the value of has to be chosen large enough to tolerate the noise, and, on the other hand, it has to be chosen small enough to preserve the image sharpness and details .Thus, we can conclude that the determination of is in fact noise-dependent to some degree. Since the kind of image noise is generally *a priori* unknown, the selection of (or) is, in practice, experimentally made, usually using trial-and-error experiments .Moreover, the value of (or) is fixed for all pixel neighborhoods over the image.

FLICM fuzzy local information c-means clustering algorithm, which can handle the defect of the selection of parameter (or), as well as promoting the image segmentation performance. In FLICM, a novel fuzzy factor is defined to replace the parameter used in EnFCM and FCM_S and its variants, and the parameter used in FGFCM and its variants. The new fuzzy local neighborhood factor can automatically determine the spatial and gray level relationship and is fully free of any parameter selection. Thus, FLICM has the following attractive characteristics: 1) it is relatively independent of the types of noise, and as a consequence, it is a better choice for clustering in the absence of prior knowledge of the noise; 2) the fuzzy local constraints incorporate simultaneously both the local spatial and the local gray level relationship in a fuzzy way; 3) the fuzzy local constraints can automatically be determined, so there is no need of any parameter determination; 4) the balance among image details and noise is automatically achieved by the fuzzy local constraints The boundaries of object surfaces in a scene often lead to oriented localized changes in intensity of an image, called edges. This observation combined with a commonly held belief that edge detection is the first step in image segmentation, has fueled a long search for a good edge detection algorithm to use in image processing [11]. This search has constituted a principal area of research in low level vision and has led to a steady stream of edge detection algorithms published in the image processing journals over the last two decades. Even recently, new edge detection algorithms are published each year. Edge detection of an image reduces significantly the amount of data and filters out information that may be regarded as less relevant, preserving the important structural properties of an image. Therefore, edges detected from its original image contain major information, which only needs a small amount of memory to store. The purpose of detecting sharp changes in image brightness is to capture important events and changes in properties of the world.

For an image formation model, discontinuities in image brightness are likely to correspond to a) Discontinuities in depth b) Discontinuities in surface orientation c) Changes in material properties d) Variations in scene illumination e) Grayness ambiguity f) Vague knowledge. In the ideal case, the result of applying an edge detector to an image may lead to a set of connected curves that indicates the boundaries of objects, the boundaries of surface marking as well curves that correspond to discontinuities in surface orientation. If the edge detection step is successful, the subsequent task of interpreting the information contents in the original image may therefore be substantially simplified. Unfortunately, however, it is not always possible to obtain such ideal edges from real life images of moderate complexity. Edges extracted from non-trivial images are often hampered by fragmentation i.e. the edge curves are not connected, missing edge segments; false edges etc., which complicate the subsequent task of interpreting the image data. Mathematical Morphology is a powerful tool for dealing with various problems in image processing and computer vision [4,9].It was introduced in [9] as a technique for analyzing geometric structure of metallic and geologic samples. It was extended to image analysis in [5, 10]. Mathematical morphology is a very important theory, whose operation must be defined by set arithmetic. Therefore, the image which will be processed by mathematical morphology theory must been changed into set. Mathematical morphology is composed by a series of morphological algebraic arithmetic operators. The basic morphological operations, namely erosion, dilation, opening, closing etc. are used for detecting, modifying, manipulating the features present in the image based on their shapes. The shape and the size of SE play crucial roles in such type of processing and are therefore chosen according to the need and purpose of the associated application. Usually, people use single and symmetrical structure elements morphology to detect image edge. But they are difficult to detect complex edge feature, because they are only sensitive to image edge which has the same direction of structure elements and are not so effective to the edge which has the direction other than the structure elements in [1, 2, 3].In this paper, a novel multi-structure elements (MSE) morphology algorithm is proposed to detect the edge of image

2. WATERSHED METHOD

The watershed transform [12, 13] is a popular segmentation method coming from the field of mathematical morphology. The intuitive description of this transform is quite simple: if we consider the image as a topographic relief, where the height of each point is directly related to its gray level, and consider rain gradually falling on the terrain, then the watersheds are the lines that separate the lakes called *catchment basins* that form.

Generally, the watershed transform is computed on the gradient of the original image, so that the catchment basin boundaries are located at high gradient points. The watershed transform has been widely used in many fields of image processing, including medical image segmentation, due to the number of advantages that it possesses: it is a simple, intuitive method, it is fast and can be parallelized [14, 15] and almost linear speedup was reported for a number of processors up to 64 and it produces a complete division of the image in separated regions even if the contrast is poor, thus avoiding the need for any kind of contour joining. Furthermore, several researchers have proposed techniques to embed the watershed transform in a multiscale framework, thus providing the advantages of these representations [16, 17]. A simplest morphological water shed method is gradient method.

2.1 Morphological Gradient

The morphological gradient m of a function f is defined by:

$$m(p) \square [(p \square S) \square (p \square S)] \quad (1)$$

Where $(p \square S)(i) \square Sup(p(j))$ is the dilation of f at the point x and $(p \square S)(i) \square Inf(p(j))$ is the erosion of f and S would be the detection of obstacles but the main problem is structuring element applied on image. Some important drawbacks have been exist, some most important are as follows.

First is Over segmentation, when the watershed transform infers catchments basins from the gradient of the image, the result of the watershed transform contains a myriad of small regions, which makes this result hardly useful. The use of a marker image [18] to reduce the number of minima of the image and thus the number of regions is the most commonly used solution. Also interesting is the utilization of a scale space approach to select the interesting regions using different filters (morphological operations [19], or nonlinear diffusion [20]).

Second is Sensitivity to noise, *the* Local variations of the image can change the result dramatically, this effect is worsened by the use of high pass filters to estimate the gradient which amplify the noise. Third is Poor detection of significant areas with low contrast boundaries if the signal to noise ratio is not high enough at the contour of interest the watershed transform will be unable to detect it accurately.

Furthermore the watershed transform naturally detects the contours with higher value between markers which are not always the contours of interest and fourth is Poor detection of thin structures, When the watershed transform is applied on the gradient image the smoothing associated with gradient estimation together with usual approach of storing gradient values only at the image pixel positions rather than with sub-pixel accuracy make it difficult to detect thin catchments basin areas. Often this is critical for successful segmentation of images.

2.2. Marker Algorithm

The procedure can be enhanced by defining markers for the objects to be extracted. These markers are obtained by various means which is described as follows, Let R be the set of markers $R \square U_i R_i$ Where R is a

connected components $(Ri \cap Rj) \square \square \square, i \square \square j)$.

Consider the function g defined by g = (1-k_m) Where u is the upper limit of the gradient m and K_M indicator function of R and the contours of the marked objects are watershed lines. This marking technique is Nonparametric and is simply based on the difference of Contrast between the object and its border. The Regularized gradient of size s of the function p is the transform defined by the following procedure

2.2.1. Algorithm

Step1: Read gray level Image size of N XM.
Step2: Compute Morphological Gradient h_i
Step3: Erode h_i with structuring element Si- 1. (Ei-1)
Step 4: Dilate E_{i-1} with Structuring element S_{i+1}. (D_{i+1})
Step5: Compute Difference of Morphologic al gradient, h_i and D_{i+1} (h_{i+1})
Step 6: Erode h_{i+1}(u_i)

This operation depends on size parameter. The main advantage of this method is its ability to take into account the variations of the initial function. The watershed of the supmax of u_i (w) is less over segmented than the watershed of h. This segmentation can now be used for extracting a coarse marker of the image. This marker is obtained by selecting the catchments basin of w located at the other end of the Image. This marker is smoothed and an outer marker is built in order to mark the region of the image which does not belong to the image. These Two markers are used to modify the gradient h. The divide lines of the modified gradient are the contours of the object. Marker is a connected component in the image region and used in watersheds for edge detection. Image markers are obtained for image simplification. A simplified image S is built starting from the image F and its gradient G(F).

Let's consider the minima M of G and let's define a function h as follows:

$h=F.P_M$ where P_M is the indicator function of M. Now compute the reconstruction of h by dilation inside the catchment basins. This operation produces an image where each basin of gradient is valued. This valuation leads to a simplified image s made of tiles of constant grey values. This gradient will be null everywhere except on the divide lines of g where it is equal to the absolute difference between the grey-tone values of catchment basins CB_i and CB_j separated by G_{ij}.

$$\text{Grad}\ (G_{ij}) = \left| F_i - F_j \right| \qquad (2)$$

This gradient image is then used to define a new function V.

$$X_i(v) = \{x : V(x) \le i\} \qquad (3)$$

$$X_i(v) = \bigcup_j CB_j \qquad (4)$$

Where, CB_j are the catchment basins adjacent to any arc with a watershed of the gradient less or equal to i. The watershed functions point-out the regions of the image surrounded by brighter contrast edges. In this approach, image segmentation is composed of two independent steps .The first and most critical step consists in finding markers for the objects to be extracted. The second one Consists of modifying the gradient function and computing the watersheds. The main drawback of this technique is identification of markers and SE is very difficult.

3. NOVEL METHOD

The selection of structure element is a key factor in morphological image processing. The size and shape of SE decide the final result of detected edges. The basic theory of multi-structure elements morphology is to construct different structure elements in the same square window and these structures elements comprise almost all the line extending directions in the square window.

Let {F(m, n)} (m, n ϵ Z) is a digital image, and (m,n) is its centre, then structure elements in (2N+1) × (2N+1) square window can be denoted by:

$$A_i = \{F(m \pm m1, n \pm n1), \theta_i = i*\alpha, -N \le m1, n1 \le N\} \qquad (5)$$

Where i=1, 2, ----4N-1, α=180/4N, $\varnothing_i$ is the direction angle of SE

In this paper, we choose N=2, then in the 5×5 square window, the direction angles of all structure elements are ø= 0^0, 22.5^0, 45^0, 67.5^0, 90^0, 112.5^0, 135^0 and 157.5^0 And these structure elements are shown in Fig.1, where "1" denotes the components of SE. In fact, structure elements A_i can be got by decomposing 5×5 square SE A as shown in Fig.2. Therefore, A_i and A satisfies:

$$A = \bigcup A_i \qquad (6)$$

0	0	0	0	0
0	0	0	0	0
1	1	1	1	1
0	0	0	0	0
0	0	0	0	0

Fig.1a

0	0	0	0	0
0	0	0	0	1
0	0	1	0	0
1	0	0	0	0
0	0	0	0	0

Fig.1b

0	0	0	0	1
0	0	0	1	0
0	0	1	0	0
0	1	0	0	0
1	0	0	0	0

Fig.1c

0	0	0	1	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	1	0	0	0

Fig.1d

1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

Fig.1e

0	0	0	0	0
1	0	0	0	0
0	0	1	0	0
0	0	0	0	1
0	0	0	0	0

Fig.1f

0	1	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	0	0	1	0

Fig.1g

0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0

Fig.1h

Fig1

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

Fig2

Step1: pre process the Image to eliminate misclassified regions in the image

$$A = 2 * b - c \qquad (7)$$

Where b and c are

$$b = \sum X_i H_i(F) / M$$

$$c = b - \max(abs(b - x_{max}), abs(b - x_{min}))$$

Where X_{max} and X_{min} are the maximum and minimum gray values of mask and Hi (F) is the frequency of occurrence of X_i.

Step2: Construct structure elements A_i of different directions according to the method presented above.
Step3: By taking the structure elements got in step2 respectively to detect the edges E_i (F) of original image by morphological gradient edge detector.

Step4: Based on every detected edge E_i (F) in step3, use synthetic weighted method to calculate final detected edge by

$$E(F) = \sum_{i=1}^{M} w_i E_i(F) \qquad (8)$$

Where E(F) is the possible detected edge of original image, M is the number of structure elements and w_i is the weight of different detected edge information.
It can be

calculated by $W_i = 1/M$.

Step 5: To find fine edges divide original image by edge image and multiply by its average in accordance with equation

$$D(x, y) = \left[f(x, y) / E(x, y) \right] * E^1(x, y) \qquad (9)$$

Where

x, y – pixel coordinates
D-resultant edge image
E-edge image from step3
E^1- average of edge Image E

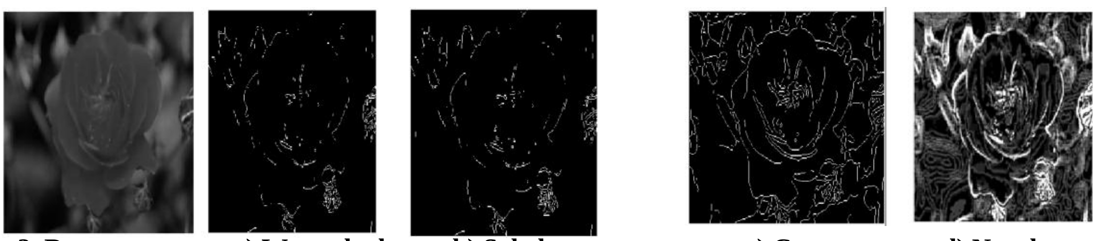
The division of the original images by its average reveals the differences between these two images. Due to image borders blur while average filtration the differences are especially visible in case of edge whilst fire images areas they are almost unrecognizable and which makes image intensity equals original image average intensity so the result of the division is regarded to be images of edges.

4. EXPERIMENTAL RESULTS

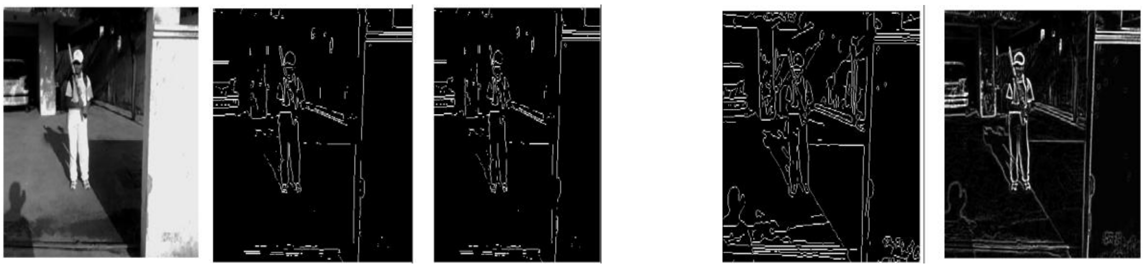
The experiments are carried out to evaluate the performance of proposed method with existing methods. The proposed method has also been tested on a wide range of natural and synthetic 512X512 pixel 8-bit gray-scale images with increasing complexity levels. The given images are containing intensity, texture and illusory boundaries respectively. This section constructed the edges for these different image attributes. The final segmentation results are illustrated. As can be seen, these images, which traditionally require different algorithms to segment, can now be processed using the multi-structure elements morphology of eight different directions. In these images, the average gray scale of eight directions was equalized to prevent biased segmentation results due to leakage of the component through the filters. This method produced better results compared to traditional methods like watershed, Sobel and canny edge detecting techniques. As per visual perception analysis the pixels misclassified as a third region at the image boundary are removed by the proposed method. According to results watershed, Sobel operators produced week edges for all images and eliminated some important features in the images and discontinuity in the edge gray level intensities. Canny edge operator is more efficient for edge detection even though it produced poor edges for low contrast images and unimodel histogram images such as rose, eye and forest images which have been shown in the results. Canny is high sensitive to noise compare to other methods.

The performance of novel method is almost all same as on all test images. This method depends on suitable selection of SE. The global threshold values of various images according to the watershed method, Sobel operator, Canny operator and novel method are shown in table1 and drawn the graph1. The values and graph explains that the novel method works better for noise and complex images with optimal values for edge detection. The novel method produced good and brighter edges by retaining important features in the images. This method works smoothly even in complex structure, noise and uneven illumination. Based on the results conclusions are made.

1. Anshu **a) Watershed** **b) Sobel** **c) Canny** **d) Novel**



2. Rose **a) Watershed** **b) Sobel** **c) Canny** **d) Novel**

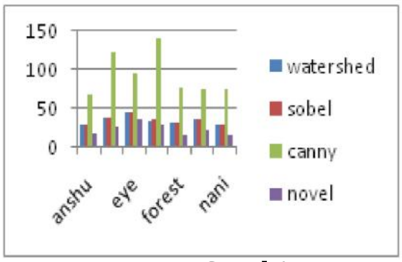


3.Nani a)Watershed b)Sobel c) Canny d) Novel

4.Lena a)Watershed b)Sobel c) Canny d) Novel

Table 1

Images	watershed	Sobel	Canny	Novel
Anshu	27	28	66	16
Rose	36	36	122	26
Eye	45	45	95	35
Lena	33	34	141	28
Forest	30	30	76	15
Pm	35	35	73	20
Nani	28	28	74	14



Graph1

5. CONCLUSIONS

The present study on Image processing is a collection of techniques that can be applied to the given images. In this paper, a novel multi-structure elements morphological edge detection algorithm is proposed to detect image edge. The technique developed is very useful for Image segmentation and classification. The selection of structure element is a key factor in morphological image processing. The size and shape of SE decide the final result of detected edges. The basic theory of multi-structure elements morphology is to construct different structure elements in the same square window. And these structures elements comprise almost all the line extending directions in the square window. The given experimental results show that the algorithm is more efficient than the usually used single and symmetrical SE morphological edge detection operator and differential edge detection operators such as watershed method , Sobel operator and canny operator,. The detected edge is more pinpointed, integral and continual, and the edge information is more abundant. Moreover, the novel proposed algorithm can filer the noise more successfully than other operators by high lighting brighter edges. Even though this method produces better results, it fails to shadow elimination of Images see in 7d. The eight different edge detection results are obtained by using morphological gradient algorithm are better edges over traditional methods.

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AUTHORS

CH.Raju received his B.Tech Degree in Computer Science and Engineering from St.Ann's College of Engineering & Technology, Chirala, and studying M.Tech in Software Engineering in St.Ann's College of Eneering & Technology, Chirala..

D.Nagesh Babu received his B.Tech Degree in **Information Technology** from Bapatla Engineering College, Bapatla. M.Tech in Computer Science and Engineering from St.Ann's College of Engineering & Technology, Chirala.. He is working as an assistant professor in the department of IT, St.Ann's College of Engineering & Technology, Chirala.. He has four years of experience.

S.Amarnath Babu received his B.Tech Degree in **CSE** from Bapatla Engineering College, Bapatla M.Tech in Computer Science and Engineering from JNTU, Hyderabad.. He is working as an professor and HOD in the department of IT, St.Ann's College of Engineering & Technology,Chirala.. He has eight years of Experience and he attended for several national/international conferences.