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Empirical Evaluation of Suitable Segmentation Algorithms for IR Images

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Abstract

Image segmentation is the first stage of processing in many practical computer vision systems. Development of segmentation algorithms has attracted considerable research interest, relatively little work has been published on the subject of their evaluation. Hence this paper enumerates and reviews mainly the image segmentation algorithms namely Otsu, Fuzzy C means, Global Active Contour / Snake model and Watershed. These suitable segmentation methods are implemented for IR images and are evaluated based on the parameters. The parameters are Variation Of Information (VOI), Global Consistency Error (GCE) and Probabilistic Rand Index (PRI). The objective of the paper is to identify the best segmentation algorithm that is suitable for IR images. From the experimentation and evaluation it is observed that the Global Active Contour/Snake model works better compared to other methods for IR images.

Keywords: *IR Image, Segmentation, Otsu, Global Active Contour/Snake, Fuzzy C Means, Watershed.*

1. Introduction

Infrared heat wave image is different from the visible light images. It reflects the distribution of the object surface temperature and latent characteristics of material form. The infrared heat radiation due to the imperfections of the system will bring a variety of noise in the imaging process. The noise of complex distribution of infrared images have made the signal to noise ratio lower than visible light images. In addition, there are still non-uniformity and low-resolution features in infrared images, which result in a higher demand to infrared image segmentation.

Segmentation is an essential pre-processing step for many image analysis applications. From the segmentation results, it is possible to identify regions of interest and objects in the scene, which is very beneficial to the subsequent image analysis or annotation. The aim is to partition the image into a finite number of semantically important regions. In this paper four types of segmentation methods, Watershed [5], Otsu [7], Fuzzy C means [1] and Global active Contour\snake model [10] are used and compared using evaluation parameters. The parameters are Probabilistic Rand Index (PRI)[12] counts the fraction of pairs of pixels whose labellings are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variations in human perception. Global Consistency Error (GCE)[15] measures the extent to which one segmentation can be viewed as a refinement of the other. Segmentations that are related in this manner are considered to be consistent, since they could represent the same natural image segmented at different scales. Variation Of Information (VOI)[11] defines the distance between two segmentations as the average conditional entropy of one segmentation given the other, and thus roughly measures the amount of randomness in one segmentation, which cannot be explained by the other.

In an effort to compare the performance of current segmentation algorithms to human perceptual grouping as well as understand the cognitive processes that govern grouping of visual elements in images, much work has gone into hand-labeled segmentations of IR images. The above segmentation algorithms mainly are applied for Infrared, and for some GPR and X-ray images.

In the next section, the theoretical foundation is given for infrared image segmentation algorithms. Section 3 gives the theoretical explanation of four parameters used to evaluate the segmentation methods. Section 4 gives the experimental results obtained by using some benchmark pictures of IR, GPR, and X-Ray. Finally, conclusions and discussion are given.

2. Segmentation Algorithms

A variety of segmentation algorithms are available in the literature. Out of which, four distinct algorithms are presented with details. They are as follows:

i. Watershed Segmentation,
ii. Global Active Contour / Snake Model,
iii. Fuzzy C Means (FCM) and
iv. Otsu.

2.1 Watershed Segmentation

Watershed segmentation is a morphological based method of image segmentation. The gradient magnitude of an image is considered as a topographic surface for the watershed transformation. Watershed lines can be found by different ways. The complete division of the image through watershed transformation relies mostly on a good estimation of image gradients. The result of the watershed transform is degraded by the background noise and it produces the over-segmentation. Moreover, under segmentation is produced by low-contrast edges that generate small magnitude gradients, causing distinct regions to be erroneously merged.

Watershed transformation is a morphological based tool for image segmentation. In grey scale mathematical morphology, the watershed transformation for image segmentation is originally proposed by Digabel and Lantuejoul (1977) and later improved by Li et. al. (2003). The watershed transform can be classified as a region-based segmentation approach [6].

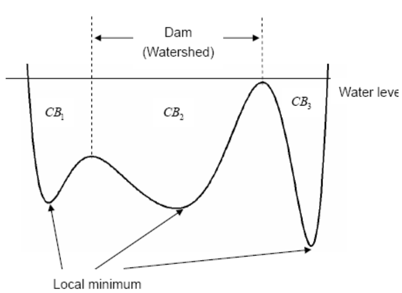


Figure 1: Illustration of immersion process of watershed transforms. (CB is for catchment basins)

The idea of watershed can be viewed as a landscape immersed in a lake catchment basins filled with water starting at each local minimum. Dams must be built where the water coming from different catchment basins may be meeting in order to avoid the merging of catchment basins. The watershed lines are defined by the catchment basins divided by the dam at the highest level where the water can reach the landscape. As a result, watershed lines can separate individual catchment basins in the landscape. The idea is described in Figure 1, which describes the flooding or rain falling process of watershed algorithm (Hsiesh, 2006). The process of rain falling is described in Figure 2.

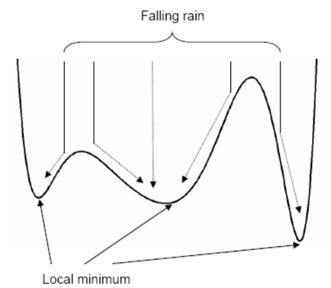


Figure 2: Illustrations of flooding (rain-falling) process of watershed transform.

2.2 Global Active Contour / Snake Model

The active contour/snake model is one of the most successful variation models in image segmentation. It consists of evolving a contour in images towards the boundaries of objects. This new formulation is said geometrically intrinsic because the proposed snake energy is invariant with respect to the curve parameterization. The model is defined by the following minimization problem:

$$\min c\left\{E_{GAC}(C) = \int_0^{L(C)} g\left(\left|\nabla I_0(C(s))\right|\right)ds\right\}, \quad (1)$$

where ds is the Euclidean element of length and $L(C)$ is the length of the curve C defined by $L(C) = \int_0^{L(C)} ds$ Hence, the energy functional above in equation(1) is actually a new length obtained by weighting the Euclidean element of length ds by the function g which contains information concerning the boundaries of objects . The function g is an edge indicator function that vanishes at object boundaries such as

$$g\left(\left|\nabla I_0\right|\right) = \frac{1}{1+\beta\left|\nabla I_0\right|^2}, \quad (2)$$

where I_0 is the original image and β is an arbitrary positive constant. The calculus of variations provides us the Euler–Lagrange equation of the functional E_{GAC} and the gradient descent method gives us the flow that minimizes as fast as possible E_{GAC} [9].

2.3 Fuzzy C Means (FCM)

The FCM method applied to image segmentation is a procedure of the label following an unsupervised fuzzy clustering. It suits for the uncertain and ambiguous characteristic in images. However the FCM exploits the homogeneity of data only in the feature space and does not adapt to their local characteristics. The FCM algorithm is an iterative algorithm that finds clusters in data and uses the concept of fuzzy membership instead of assigning a pixel to a single cluster. Each pixel will have different membership values on each cluster. The Fuzzy C-Means [2] attempts to find clusters in the data by minimizing an objective function shown in the equation (3) below:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^{m} \left| x_i - c_j \right|^2 \quad (3)$$

hence J is the objective function. After one iteration of the algorithm the value of J is smaller than before. It means the algorithm is converging or getting closer to a good separation of pixels into clusters.

N is the number of pixels in the image.
C is the number of clusters used in the algorithm, and which must be decided before execution.
μ is the membership table -- a table of NxC entries that contains the membership values of each data point and each cluster.
m is a fuzziness factor (a value larger than 1).
x_i is the i^{th} pixel in N.
c_j is j^{th} cluster in C.
$|x_i - c_j|$ is the Euclidean distance between x_i and c_j.

2.4 Otsu method

Otsu method is based on the optimal thresholding for image segmentation. The minimization of the criterion function is the major focus. The criterion for Otsu [8] is the minimization of the within-group variance of the two groups of pixels separated by the threshold. The function of the Otsu method is as follows:

$$\sigma^2 within(T) = n_B(T)\sigma_B^2(T) + n_0(T)\sigma_0^2(T) \quad (4)$$

where

$$n_B(T) = \sum_{i=0}^{T-1} p(i)$$

$$n_0(T) = \sum_{i=T}^{N-1} p(i)$$

$\sigma_S^2(T)$ = the variance of the pixel in the background (<T)

$\sigma_0^2(T)$ = the variance of the pixel in the foreground (>T) and [0 ,N-1] is the range of intensity levels.

3. Parameters Used for Evaluation

Unsupervised image segmentation is an important component in many image understanding algorithms and practical vision systems. However, the evaluation of segmentation algorithms thus far have been largely subjective, leaving a system designer to judge the effectiveness of a technique based only on intuition and results in the form of a few example segmented images. This is largely due to image segmentation being an ill-defined problem and there is no unique ground-truth segmentation of an image against which the output of an algorithm may be compared.

Segmentation algorithms taken are generally applicable to all images, and different algorithms are not equally suitable for a particular application. Here needs a way of comparing them, so that the better ones can be selected. Evaluation results vary significantly between different evaluators, because each evaluator may have distinct standards for measuring the quality of the segmentation.

Any evaluation metric desired should take into account the following effects:

- Over-segmentation. A region of the reference is represented by two or more regions in the examined segmentation.
- Under-segmentation. Two or more regions of the reference are represented by a single region in the examined segmentation.
- Inaccurate boundary localization. Ground truth is usually produced by humans that segment at different granularities.
- Different number of segments. One needs to compare two segmentations when they have different numbers of segments.

So, this paper presents three different parameters that are used to evaluate the experimented segmentation methods. The Parameters Used for Evaluation are as follows:

i. Global Consistency Error (GCE)
ii. The Probabilistic Rand Index (PRI)
iii. Variation Of Information (VOI)

3.1 Global Consistency Error

It is a Region-based Segmentation Consistency, which measures to quantify the consistency between image segmentations of differing granularities. It is used to compare the results of algorithms to a database of manually segmented images. Let S and S' be two segmentations as before. For a given point x_i (pixel), consider the classes (segments) that contain x_i in S and S_0. These sets are denoted in the form of pixels by C (S, x_i) and C (S_0, x_i) respectively.

Following [5], the local refinement error (LRE) is then defined at point x_i as:

$$LRE(S,S',x_i)=\frac{|C(S,x_i)\setminus C(S',x_i)|}{|C(S,x_i)|} \tag{5}$$

Global Consistency Error (GCE) forces all local refinements to be in the same direction and is defined as:

$$GCE(S,S')=\frac{1}{N}\min\left\{\sum LRE(S,S',x_i),\sum LRE(S',S,x_i)\right\} \tag{6}$$

It measures the extent to which one segmentation can be viewed as a refinement of the other. Segmentations that are related in this manner are considered to be consistent, since they could represent the same natural image segmented at different scales.

3.2 The Probabilistic Rand Index (PRI)

Rand Index is the function that converts the problem of comparing two partitions with possibly differing number of classes into a problem of computing pair wise label relationships.

PRI counts the fraction of pairs of pixels whose labelling are consistent between the computed segmentation and the ground truth, averaging across multiple ground truth segmentations to account for scale variation in human perception.

It is a measure that combines the desirable statistical properties of the Rand index with the ability to accommodate refinements appropriately. Since the latter property is relevant primarily when quantifying consistency of image segmentation results.

Consider a set of manually segmented (ground truth) images $\{S_1, S_2, \ldots, S_K\}$ corresponding to an image $X = \{x_1, x_2, \ldots x_i, \ldots, x_N\}$, where a subscript indexes one of N pixels. S_{test} is the segmentation of a test image, and then PRI is defined as:

$$PR\left(S_{test,}\{S_k\}\right)=\frac{1}{\binom{N}{2}}\sum_{\substack{i,j\\ i<j}}\left[I\left(l_i^{S_{test}}=l_j^{S_{test}}\right)p_{ij}+I\left(l_i^{S_{test}}\neq l_j^{S_{test}}\right)\left(1-p_{ij}\right)\right]$$

$$p_{ij}=P\left(l_i=l_j\right)=\frac{1}{K}\sum_{k=1}^{K}I\left(l_i^k=l_j^k\right) \tag{7}$$

This measure takes values in [0, 1] – 0 when S and $\{S_1, S_2, \ldots, S_K\}$ have no similarities and 1 when all segmentations are identical (i.e. when S consists of a single cluster and each segmentation in $\{S_1, S_2, \ldots, S_K\}$ consists only of clusters containing single points, or Vice versa).

3.3 The Variation of Information (VOI)

It measures the sum of information loss and information gain between the two clustering, and thus it roughly measures the extent to which one clustering can explain the other. The VOI metric is nonnegative, with lower values indicating greater similarity. It is based on relationship between a point and its cluster. It uses mutual information metric and entropy to approximate the distance between two clustering across the lattice of possible clustering. More precisely, it measures the amount of information that is lost or gained in changing from one clustering to another (and, thus, can be viewed as representing the amount of randomness in one segmentation which cannot be explained by the other).

The variation of information is a measure of the distance between two clustering (partitions of elements). A clustering with clusters $X_1,X_2, , , , ,X_k$ is represented by a random variable X with X={1 ….K} such that $p_i=|X_i|/n$ i€X and $n=\sum_i X_i$ the variation of information between two clustering X and Y so represented is defined to be:

$$VI(X,Y):=H(X)=H(Y)-2I(X;Y) \tag{8}$$

where *H*(*X*) is entropy of *X* and *I*(*X*,*Y*) is mutual information between *X* and *Y*. VI(X,Y) measures how much the cluster assignment for an item in clustering X reduces the uncertainty about the item's cluster in clustering Y.

4. Experiments and Results

The segmentation methods discussed above are applied to a set of bench mark images. Annexure-I shows the segmentation results of four methods applied on twenty-five dataset images. These three metrics discussed are calculated for the four mentioned segmentation methods. Figure 1 show the application of sample IR image segmentations.

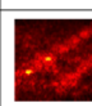
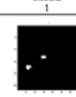
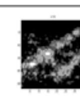
Images	Original Image	Global Active Contour Model 1	Karhunen Loeve Watershed 2	Fuzzy C means 3	Otsu 4
1					

Figure 1: Application of segmentation methods over an IR landmine image

Table 1: Sample performance measures for the segmentation results of four methods on IR landmine images presented in Figure 1.

Images& Model	***Probabilistic Rand Index***	***Global consistency Error***	***Variation of information***
1.1	0.9928	0.9935	15.8120
1.2	0.9953	0.9971	17.4327
1.3	0.9933	0.9943	16.0488
1.4	0.9945	0.9959	16.6339

Table 1 shows the parameter values of different segmentation of single image in figure 1.

Following figures 2,3,4 give comparative performance measure of four segmentation algorithms using the three evaluation parameters. From this evaluation, it is found that Global Active Contour / Snake Model segmentation is well suited for the IR images. The PRI value should be higher for an image and VOI, GCE values must be lower for an image [14].

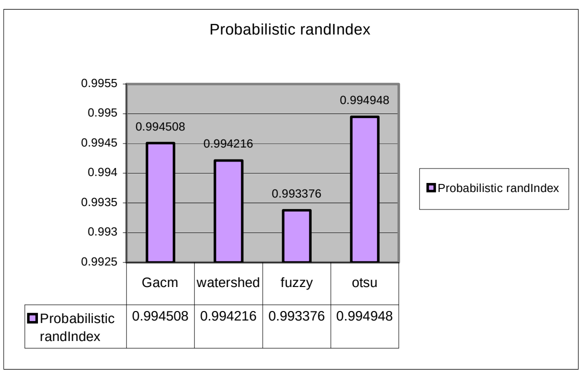


Figure 2: Evaluation graph using Probabilistic Rand Index

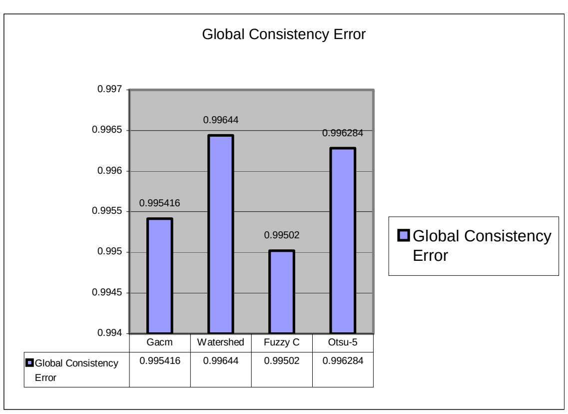


Figure 3: Evaluation graph using Global Consistency

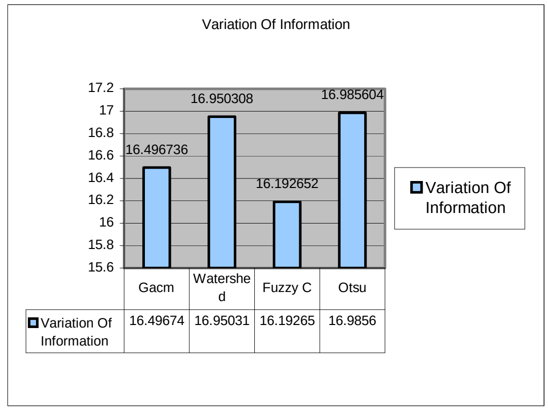


Figure 4: Evaluation graph using Variation Of Information

5. Conclusions

Since segmentation is the step important for object recognition, it is necessary to find out the best algorithms suitable for IR images. In this paper, four different segmention algorithms are experimented for set of IR images and some of X-ray and GPR images. Performance evaluation of segmented images showed that under Global active contour / snake model exhibit better performances for above said images. respectively. The experiment are conducted using matlab tool.

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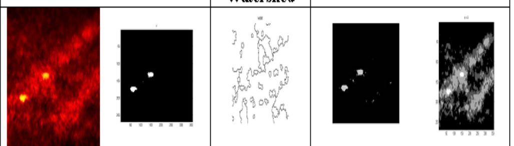
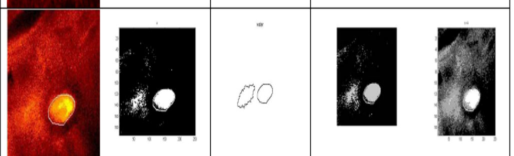
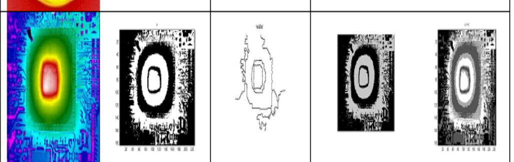
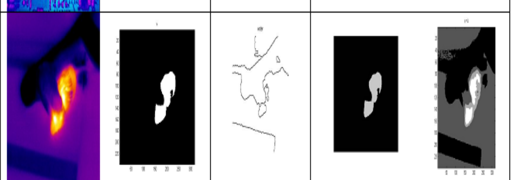
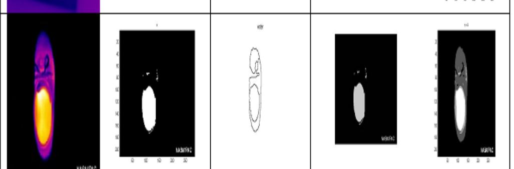
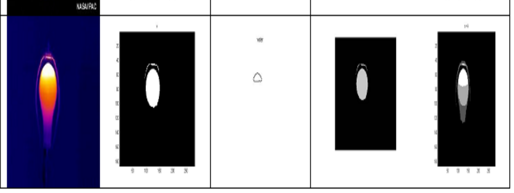
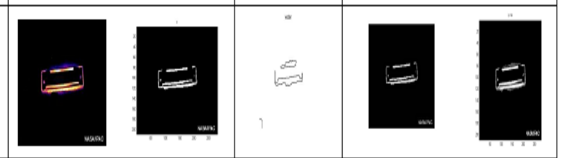
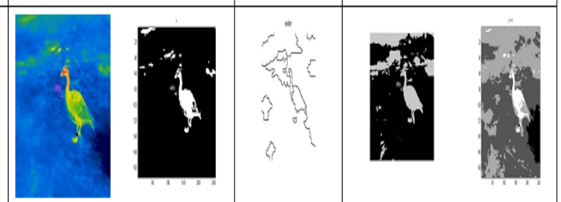
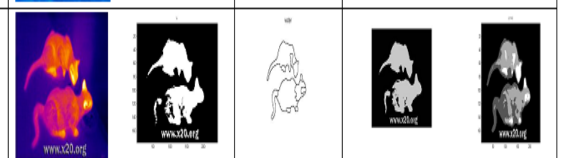
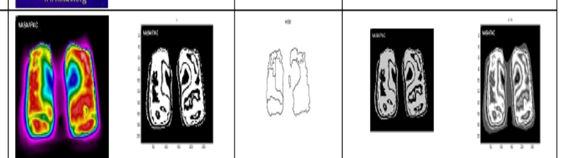
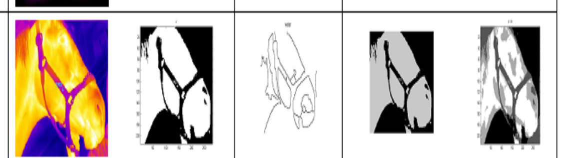
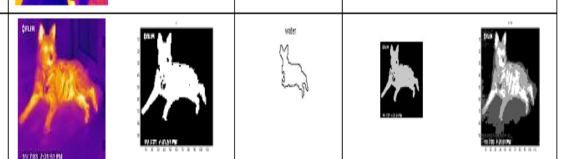
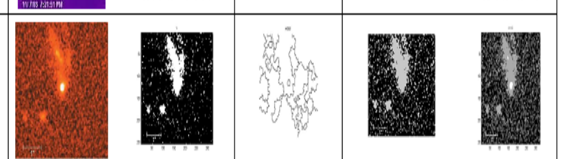
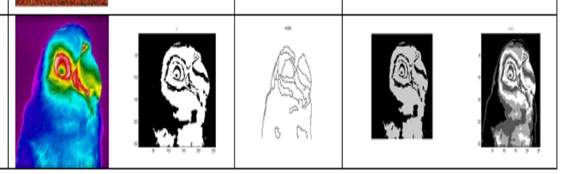
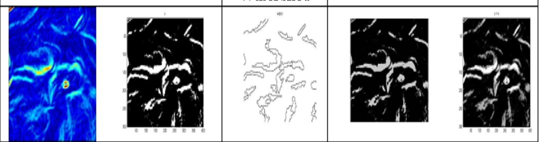
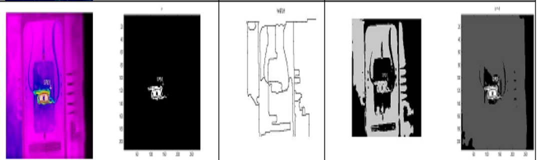
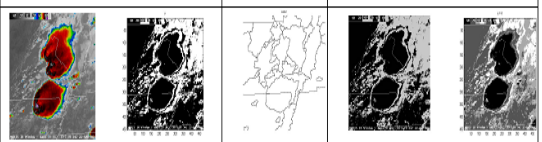
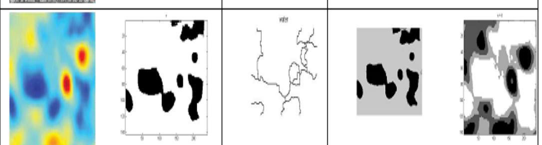
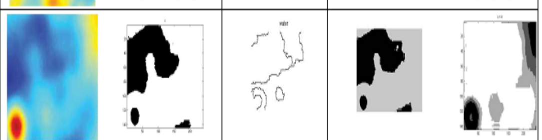
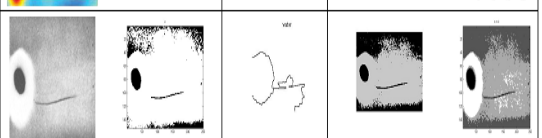
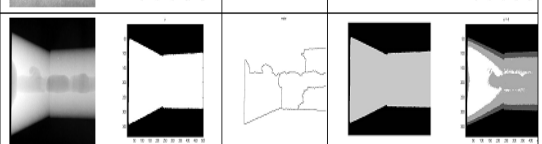
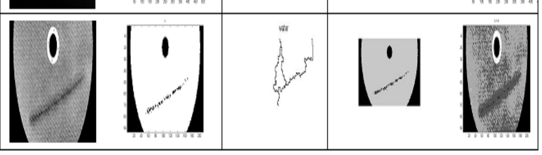
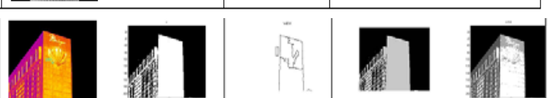
Ms.A.Sumi received MCA Degree in Kongu Arts and Science college, Erode in 2002 and M.phill Degree from Bharathiyar University, Coimbatore in 2007 respectively. She has 2 years of teaching experience and currently working as a research staff in Department of Computer Science in Avinashilingam Deemed University for women. Her research interests are Image processing, scripting and Networking.

Annexure

BENCH MARK IMAGES TAKEN FOR STUDY AND THE RESULTS OF FOUR ALGORITHMS

Images	Original Image	Global Active Contour Model	Karhunen Loeve Watershed	Fuzzy C means	Otsu
1					
2					
3					
4					
5					
6					
7					

Images	Original Image	Global Active Contour Model	Karhunen Loeve Watershed	Fuzzy C means	Otsu
8					
9					
10					
11					
12					
13					
14					
15					

Images	Original Image	Global Active Contour Model	Karhunen Loeve Watershed	Fuzzy C means	Otsu
16					
17					
18					
19					
20					
21					
22					
23					
24					
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