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A REVIEW ON MEDICAL IMAGE SEGMENTATION: TECHNIQUES AND ITS EFFICIENCY

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ABSTRACT

Image segmentation is the procedure of separating an image into significant areas based on similarity or heterogeneity measures and it is widely used in many fields that involve digital imaging including the medical field. Medical images from Computed Tomography, Magnetic Resonance Imaging and Mammogram require a proper segmentation technique to decompose the images into parts for further analysis. However, a standard methodology for any type of medical image segmentation is yet to be developed. The current image segmentation techniques and its efficiency will be evaluated in order to discover the technique that is most appropriate to be used for medical image segmentation. Researches carried out on image segmentation techniques between the periods of 2000 to 2016 are analysed and examined. This study specifically compares the techniques by analysing the performance of each algorithm on breast cancer modalities.

Keywords: *Image processing, Image segmentation, Clustering, Thresholding, Graph-based, Breast cancer.*

1.0 INTRODUCTION

The human eye and brain are visual systems that enable the ability to process visual details, as well as enabling the formation of several non-image photo response functions. In history, computer vision attempts to imitate these capabilities and has been considered as high-level image processing out with computer or software intending to decipher the physical contents of an image. This paper focuses on image segmentation, which is the process of portioning a digital image into multiple segments or regions. Globally the segmentation is used to simplify the current representation of an image into something that is more meaningful and easier to analyse.

The role of segmentation is decisive in most of the tasks requiring image analysis. The success or failure of the task is often a direct consequence of the segmentation process itself that takes place. However, a reliable and super accurate segmentation of an image is, in general, very difficult to be achieved solely by automatic means. Segmentation subdivides digital images into its component objects or regions. The process divides an image into distinct regions that are meant to correlate strongly with objects of features of interest in the image. Segmentation can also be regarded as a process of grouping together pixels that have similar attributes. On the other hand, image segmentation algorithms have evolved to a point that they can provide segmentation that agrees to a large length with human intuition. A few image segmentation techniques that are currently being used are namely Thresholding, Mean Shift segmentation (Kaftan et al., 2008), K-Means segmentation (Kanungo et al., 2002), normalized cuts (Shi and Malik, 2000a) and efficient graph-based segmentation (Felzenszwalb and Huttenlocher, 2004).

In medical application, image acquisition can affect local intensity characteristics, important biological structures may be composed of more than one tissue type, and boundaries between different tissue classes within single voxels result in intensities that are not characteristic of either tissue. The goal of most recent work in medical image segmentation is to reduce or remove the need for manual intervention. Prior knowledge and modelling of image acquisition and variation in appearance under imaging are often necessary to obtain biologically meaningful delineations (Crum, Camara, and Hill, 2006). In the image segmentation work for breast cancer that was conducted by Monica et al. (2016), the author suggests some common limitation on the segmentation that can be overcome by denoising the given input image using wavelet transform and analysis made on an inverse transformed image. Digital mammography is one of the popular medical modalities used as a diagnostic technique for detecting breast cancer. As reported in (Chakravarthi et al., 2016), the major challenge lies in developing an efficient image segmentation technique to extract a tumour to its original size and to remove the undesirable regions completely. Evaluation is generally difficult as it is possible to image phantom objects with known tissue properties; in the application of interest, the underlying tissue classification is unknown.

The Normalized Probabilistic Rand Index (NPR) measures the fraction of pixel pairs whose labels are consistent between the segmentation result and the ground truth (Wang et al., 2015). In practice, NPR can be computed in a simple form. Let S_{ground} and S_{test} be two clustering of the same image with a different number of cluster. Overlap ratio measures (e.g. Jaccard 1907, Dice 1945) apply to many situations and image segmentation is one of it. Most of them range from 0 (no overlap) to 1 (complete congruence). Unlike volume error, they are sensitive to misplacement of the segmentation label, but they are relatively insensitive to volumetric and overestimation. The dice similarity is currently more popular than the Jaccard overlap ratio. This is because Jaccard is numerically more sensitive to mismatch when there is reasonably strong overlap. Dice value presentation is more significant because they are higher for the same pair of segmentation. The major cons of both are that they are unsuitable for comparing segmentation accuracy on the object or image that differ in size (Rohlfing et al., 2004). The best way to measure the accuracy of a segmentation depends on the consequences that any error in the segmentation might have.

Therefore, better evaluation techniques for image segmentation process is needed in order to maximize and improvise the current available technique. One of the biggest problems in medical image segmentation is the lack of gold standards for many segmentation applications. Time-consuming manual segmentation with its inherent variability remains necessary but is often limited by resources and expertise. Big data system can be used to enhance powerful medical image analysis. Understanding their behaviors in this context can lead to many advantages such as superior infrastructure configurations to optimized parallel algorithm implementations (Zhang et al., 2016). In recent years, most of the primitive segmentation methods have been paired with optimization algorithm in order to achieve better segmentation result as shown in (Raja et al., 2015; Suresh and Shyam, 2016). Besides using optimization algorithm, there is also an attempt to enhance input image quality by using any pre-processing image enhancement algorithm as discussed in (Elakkia and Narendran, 2016). The comparative study of various image processing techniques has been given in tabular form by Jeyavathana et al. (2016).

Based on the researches done between 2000 to 2016, 68% is related to image segmentation. 46% of the study on image segmentation is related to and used for medical purposes. Among the works that discussed about medical image segmentations can be found in (Bindu and Prasad, 2012; Crum et al., 2006; Huang et al., 2012; Liu and Zeng, 2012; Mahmood et al., 2012; Patel and Sinha, 2010; Raja et al., 2015; Swetha and Bindu, 2015; Zhang et al., 2015, Zhou et al., 2016). Image segmentation in medical field represents, respectively, the computation time required for segmenting each scene and the computation time required for one-time (and not per-scene) algorithm training. Selection of an appropriate segmentation technique largely depends on the type of images and application areas. Possibly the human being is the best judge for this.

This paper is structured as follows: Section 2 briefly explains the most currently popular image segmentation techniques that is currently being used by the industry and research community. The results of each image segmentation technique that had been applied on the medical image will be discussed in Section 3. Section 4 discusses some the future research and recommendations in image segmentation. Finally, the conclusion is presented in Section 5.

2.0 IMAGE SEGMENTATION TECHNIQUES

There are many image segmentation techniques that been maturing over time and only three are selected to be further discussed in this publication namely: Thresholding (Otsu's Method) (Bindu and Prasad, 2012), Clustering method (K-Means (Patel and Sinha, 2010), Mean Shift (Zhou et al., 2011) and Graph-Based Segmentation (Normalized cut (Shi and Malik, 2000b) and Efficient graph-based method (Felzenszwalb and Huttenlocher, 2004)) which are the most popular in medical image segmentation.

2.1 Thresholding Method

Thresholding method is based on a clip- level (or a threshold value) to turn a gray-scale image into a binary image. The pixels are portioned depending in their intensity value and when the image is portioned into several sub-regions and a threshold is determined for each of the sub-regions, it is referred to as local thresholding (Pal and Pal, 1993). Bi-level thresholding is the process when the image is portioned into two regions, which are an object (black) and background (white). Multithresholding is used in Sathya and Kayalvizhi (2011), when the image is composed of several objects with distinct surface characteristics (for a light intensity image, object with similar coefficient or reflection, for a range image there can be objects with different depths) one needs several thresholds for segmentation. One of the popular methods in thresholding is Otsu's Method (Smith et al., 1979). This method is aimed at finding the optimal value for the global threshold *T* with the global variance:

$$\frac{o^2}{G} = \sum_{i=0}^{L-1}(i - mG)^2 . pi \tag{1}$$

Otsu's Method is based on the interclass variance maximization where well threshold classes have well-discriminated intensity values. Using $k, 0 < k < L - 1$, (where L is intensity levels) as threshold, $T = k$: i) Two classes: C1 (pixels in $[0, k]$ and C2 (pixels in$[k + 1, L - 1]$); ii) *P1 = P(C1) = Pk i=0 pi*, probability of the class C1; iii) $m1$ represents the mean intensity of the pixel in C1 which is calculated by the following:

$$m_1 = \sum_{i=0}^{k} i . P(i|c_i)$$

$$= \sum_{i=0}^{k} i \frac{P(C_1|i)P(i)}{P(C_1)}$$

$$= \frac{1}{P_1}\sum_{i=0}^{k} i . p_i \tag{2}$$

where $P(C_1|i) = 1. P(i) = p_i \ e \ P(C_1) = P_1$

iv) Hence, the global mean is derived by:

$$P_1 m_1 + P_2 m_2 = m_G \tag{3}$$

$$P_1 + P_2 = 1$$

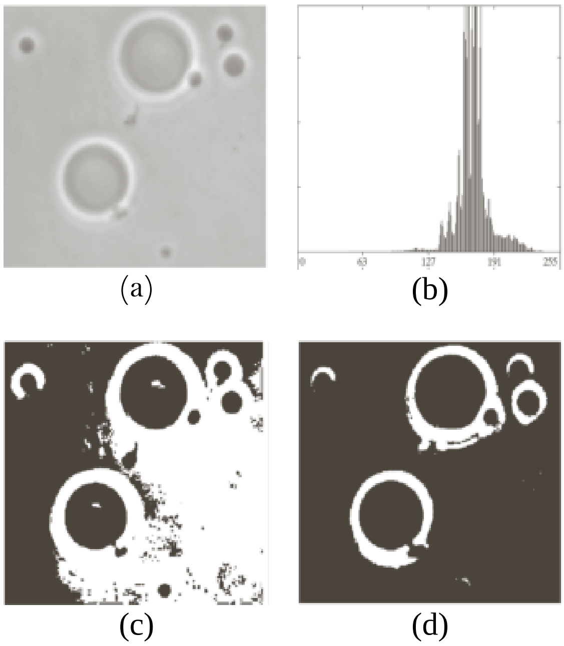


Figure 1. Otsu's Method Output: (a) Original Cell Image; (b) Histogram of (a); (c) Global Threshold; (d) Otsu’s Method (Smith et al. 1979).

Figure 1 shows the output of Otsu’s method and which consists of: a) The original image; b) Histogram of (a); c) Global threshold: $T = 169, n = 0.467$; d) Otsu’s Method: $T = 181, n = 0.944$. There are several known issues when using Otsu's method, firstly when dealing with the grey level images, it discontinues the conventional Otsu algorithm resulting in the inability to find a good union of a threshold to the global optimum. Even though the Otsu algorithm does not make any hypothesis on the probability density function and state the two objective and background probability density function, it presumes the two-probability density function and can be stated by making use of the two statistics. Secondly, Otsu's method also failed when the global distribution of the target and background are varied extensively (Makkar, 2014). In the opinion of the author, this method must be customized if more than two classes exist in the image, in order to decide multilevel threshold. This loom allows the largest among-class variance value and the least in-class variance value.

In Suresh and Shyam (2016) works, they proposed a computationally efficient image segmentation algorithm called $CS_{McCulloch}$ incorporating McCulloch's method for $lévy\ flight$ generation in Cuckoo Search algorithm. They investigated the impact of Mantegna's method for $lévy\ flight$ generation in CS algorithm ($CS_{Mategna}$) by comparing it with conventional CS algorithm using Kapur entropy and Otsu's method. Nature inspired algorithm, Cuckoo Search (CS) was implemented in order to solve the significant problem in thresholding method which is selecting the optimum threshold values. In recent years, many researchers try to incorporated optimization algorithm in Otsu's interclass variance in order to get the optimum threshold value in their segmentation process using Otsu's conventional method. The major limitation of the proposed technique is that although it improved computational complexity for all the cases investigated, the segmentation quality deteriorated for lower levels of thresholding. There are also enhanced thresholding algorithm as discussed by Wang et al. (2016), where the algorithm is based on minimizing piecewise constant Mumford-Shah functional in which the contour length (or parameter) is approximated by a non-local multi-phase energy.

2.2 Clustering Method

Clustering technique is also one of the most popular choices in image segmentation process because they are instinctive and easy to implement. Two most famous clustering technique are K-Means (Patel and Sinha, 2010) and Mean Shift (Zhou et al., 2011). But, it is common that clustering image segmentation has many problems as discussed in (Oliver et al., 2006). For example, the amount of region of the image has to be known early and as well the different initial seed placement could affect the process outcome. In K-Means (Kanungo et al., 2002; Pantofaru and Hebert, 2005), it works by assigning each of the N points (xj), to cluster by nearest μi. The algorithm then re-compute the μi mean of each cluster from its member points. If no mean is changed more than some $\sum$, then the process should stop because it means that the algorithm has converged. Due to its presence in Matlab, K-Means is simple and fast to be implemented plus it converges to a local minimum of the error functions. The drawbacks of using K-Means are: i) need to pick K, ii) Sensitive to initialization, iii) Only finds 'spherical' cluster. Figure 2 depicts the overall K-Means process to separate samples into *n* groups of equal variance:

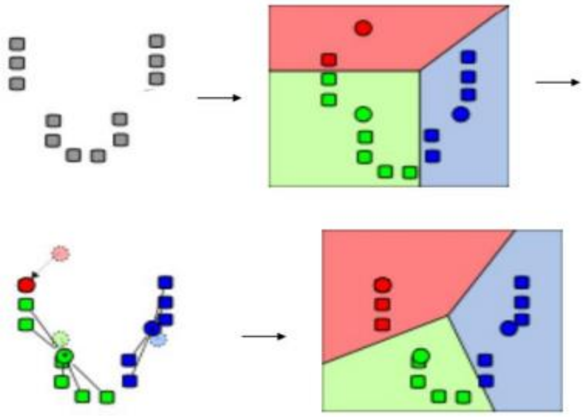


Figure 2. Overall K-mean process (*https://en.wikipedia.org/wiki/K-means_clustering*)

In a study by Yao et al. (2013), the authors proposed a new fish image segmentation method which is the combination of the K-means clustering segmentation algorithm and mathematical morphology. They firstly improved the traditional K-means which the best number of clusters is determined by the number of gray histogram peaks, and the cluster centers data is filtered by comparing the mean with the threshold decided by Otsu interclass variance. Secondly, they apply the opening and closing operations of the mathematical morphology that are used to get the contour of the fish body. Results from the proposed algorithm showed that the proposed algorithm realized the separation between the fish and the background in the conditions of complex background. There is also an enhanced K-Means algorithm proposed by Viola (2016) where the author utilized the primitive K-Means clustering algorithm to segment energy consumption behavior in three clusters, thus this study proves that image segmentation is also capable of giving reasoning rather than only dividing an image into an interested area.

Mean Shift (Pantofaru and Hebert, 2005; Zhou et al., 2011) is a nonparametric iterative algorithm or a nonparametric density gradient estimation using a generalized kernel approach. For each data point, Mean Shift defines a window around it and computes the mean of the data point. Then it shifts the centre of the window to the mean and repeats the algorithm until it converges. To date, we can say that Mean Shift is the most powerful clustering technique. Mean Shift can be summed up as: i) For each point x ii) Choose a search window iii) Compute the Mean Shift vector $m(x^t/i)$ iv) Repeat till converge. According to the Mean Shift algorithm, the complexity is $o(Tn^2)$, the first step is the most computationally expensive step. Furthermore, the means will findf the closest neighbour of a point is the most expensive operation of Mean Shift technique and larger distance result in slower processing time. Table 1 summarizes the pros and cons of both methods:

Table 1. Pros and Cons between K-Means and Mean Shift

	Pros	Cons
K-Means	• K-Means is one of most popular method. It is simple, fast and efficient. • K-means makes two broad assumptions – the number of clusters is already known • K-means is fast and has a time complexity $O(knT)$ where k is the number of clusters, *n* is the number of points and *T* is the number of iterations	• K-means is very sensitive to initialization
Mean Shift	• Mean shift is a non-parametric algorithm, which does not assume anything about number of clusters	• The larger hs the slower of processing time • Classic mean shift is computationally expensive with a time complexity $O(Tn2)$ • Mean shift is sensitive to the selection of bandwidth h

According to Mahmood et al. (2012), they use a novel Adaptive Mean Shift (AMS) algorithm for the segmentation of tissues in Magnetic Resonance (MR) brain images. The authors introduced a novel Bayesian approach for the estimation of the adaptive kernel bandwidth and investigated its impact on segmentation accuracy. The segmentation experiments were carried on both multi-modal simulated and real patient T1-weighted MR volumes with different noise characteristics and spatial inhomogeneity. In a study by Zhou et al. (2013), they fully utilized the Gradient Vector Flow (GVF) based algorithms to segment a variety of 2-D and 3-D imageries. Their proposed method is MSGVF, a mean shift based GVF segmentation algorithm that can successfully locate the correct borders. MSGVF is developed so that when the contour reaches equilibrium, the various forces resulting from the different energy terms are balanced. The proposed algorithm is accurate as it obtains an optimal solution during the iterations for energy minimization. The highlighted drawback of the proposed algorithm is that it involves a large amount of computation to achieve convergence. Even though it has been shown that numerical convergence of the evolving contour is guaranteed, the solution- rendering process is rather time-consuming.

Implementing Mean Shift clustering for statistical unsupervised learning based on density gradient ascent has been carried out in (Duong et al., 2016). The proposed automatic selection of the nearest neighbor for density gradient was demonstrated to discover the accurate number, location and shape of non-ellipsoidal clusters in multivariate data analysis and image segmentation.

2.3 Graph-Based Segmentation

There are two most outstanding methods in Graph-Based Segmentation which are Normalized Cut (Shi and Malik, 2000a) and efficient graph-based image segmentation, introduced in (Felzenszwalb and Huttenlocher, 2004). A research conducted by Shi and Malik (2000b), mentioned that the key point is image portioning must be done from the big picture downward, rather like a painter first making out the major areas and then filling in the details. Moreover, their approach is mostly related to the graph-theoretic formulation of grouping. They then proposed a new graph-theoretic criterion for measuring the goodness of an image partition- the Normalized Cut. The main ideas of Normalized Cut are to present the image as graphs: i) Node for every pixel ii) Edge between every pair of pixels iii) Each edge weighted by the affinity or similarity of the two nodes. In Efficient Graph-Based segmentation, Felzenszwalb and Huttenlocher (2004) mentioned that their method is based on selecting edges from a graph, where each pixel corresponds to a node in the graph, and certain neighbouring pixels are connected by undirected edges. The researcher has successfully worked on interactive segmentation for medical modalities including graph cut and random walk. However, as reported in (Kitrungrotsakul et al., 2015), graph cut-based organ segmentation for 3D medical modalities requires an optimization procedure of cutting the object regions on a very large scale graph, which not only consumes a large amount of memory and but also requires an expensive computational cost.

This technique also adaptively adjusted the segmentation criterion based on the degree of variability in neighbouring regions of the image thus resulting from greedy decisions that can be shown to obey certain non-obvious global properties. This method turns in $O(m \log m)$ time for m graph edges and it is also fast in practice, generally consuming in a fraction of a second. Felzenszwalb and Huttenlocher (2004) in their study has illustrated in two kinds of a graph, the first one uses the image grid to define a local neighbourhood between image pixels, and measures the difference in intensity (or color) between each pair of neighbour. The second one maps the image pixels to point in a feature space that combines the *(x, y)* location and *rgb* colour value. The algorithm produced good results using both kinds of graphs, but the latter type of graph captures the more perceptually global aspect of the image. Thus, EGB segmentation is very fast, running in almost linear time, however, suffers a lot in accuracy when compared to other established segmentation algorithms.

In addition, a study by Huang et al. (2012) presents a new graph-based method for segmenting breast tumors in US images. The proposed works constructed a graph using improved neighborhood models and taking advantages of local statistic, a new pair-wise region comparison predicate that was insensitive to noise was proposed to determine the emergence of any two adjacent sub regions. Saglam and Baykan (2015) in their work first segmented the entire image to save global features thus to obtain more accurate segmentation. Then, they extracted the intended object from the image by merging the segments that are inside the area drawn before by the author himself. It is considered a fast method but the drawback of this is the algorithm will make greedy assumptions about global criteria and will use only color differences and cluster size. There is also work such as in (Li et al., 2016) where they propose to use a max-flow algorithm to optimize a locally improved Chan-Vee model for image segmentation in the presence of intensity inhomogeneity.

2.4 Image Segmentation Efficiency and Performance

Unsupervised image segmentation process is an important component in many image analysis algorithms and computer vision fields. Even though image segmentation has moved at greater pace nowadays, but it still remains subjective, leaving system designer to judge the effectiveness of a technique based only on intuition and result in the form of a few example segmented images. One of the purposed techniques to measure the efficiency of image segmentation is Normalized Probabilistic Rand (NPR) index which is introduced in (Unnikrishnan et al., 2005). Other methods that are commonly used are Jaccard Similarity Index, Dice Similarity Coefficient and F-1 Score. The following subsection briefly discusses each of these techniques.

2.4.1 Normalized Probabilistic Rand (NPR) Index

In NPR index, the algorithm is to be evaluated by objective comparison of their segmentation results with manual segmentation (ground truth), several which are available for each image. The number generated by the NPR index for a variety of natural images corresponds to a human intuition of perceptual grouping. The significance of a measure of correctness has much to do with the baseline (ground truth) with respect to which it is expressed. For image segmentation, the baseline may be interpreted as the expected value of the index under some appropriate model of randomness in the input images. Normalized Probabilistic Rand is the extended work of Probabilistic Rand (PR). Consider the Probabilistic Rand (PR) index (Ifenthaler, 2012):

$$\mathrm{PR}(S_{test}, \{S_k\}) = \frac{1}{\binom{N}{2}} \sum_{\substack{i,j \\ i<j}} [c_{ij}p_{ij} + (1 - c_{ij})(1 - p_{ij})] \tag{4}$$

A popular strategy is to use the index normalized with respect to its baseline as:

$$Normalized\ index = \frac{Index - Expected\ index}{Maximum\ index - Expected\ index} \tag{5}$$

This causes the expected value of the normalized index to be zero and the modified index to have a larger range and hence be more sensitive. Hubert and Arabie (1985) normalized the Rand index using a baseline that assumes the segmentation is generated from a hyper geometric distribution. This tells us that (a) the segmentation process is independent, and (b) the number of pixels having a particular label is kept constant.

2.4.2 Jaccard Similarity Index

The well-known Jaccard Similarity Coefficient is a statistic used for comparing the similarity and diversity of sample sets. This kind of algorithm measures the similarity between finite sample sets, and is defined as the size of the intersection divided by the size of the union of sample sets:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A|+|B|-|A \cap B|} \tag{6}$$

(If A and B are both empty, we defined$d(A,B) = 1$)

$$0 \leq j(A,B) \leq 1$$

Padma and Giridharan (2016) evaluated the performance between segmentation methods and the overlap similarity measure using Jaccard Index. The standard Jaccard Similarity Index has been calculated. This index compares the results between manual segmentation (ground truth provided by a radiologist) and automatic segmentation (segmentation results). Jaccard index which measures the similarity between two sets is defined by:

$$Jaccard\ Index = |S_a \cap S_m| / |S_a \cup S_m| \tag{7}$$

Where S_a and S_m denote the pixels of the tumour region segmented by Padma and Giridharan (2016) method and the manual method. Value of Jaccard index lies between 0, when the two sets have no common elements, and 1, when the two sets are identical.

2.4.3 Dice Similarity Coefficient

The Dice Similarity Coefficient (DSC) was used as a statistical validation metric to evaluate the performance of both the reproducibility of manual segmentations and the spatial overlap accuracy of automated probabilistic fractional segmentations. DSC measures the spatial overlap between two segmentations, A and B target regions, and is defined as $DSC(A, B) = 2(A \cap B)/(A + B)$, where $\cap$ is the intersection. In binary manual segmentation, this coefficient may be derived from a two-by-two contingency table of segmentation classification probabilities. Theoretically, DSC is also a special case of the kappa statistic commonly used in reliability analysis, when there is a much larger number of background voxels than that of the target voxels. DSC has restricted range of [0,1] and is often close to the value 1, we have found it useful to adopt a logit transformation.

2.4.4 F-1 Score

F-1 score or also known as F-measure is a measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score:

$$F = 2 * \frac{precision * recall}{precision + recall} \tag{8}$$

F-measure is a classical and popular segmentation metric (Powers, 2007). It compares segmentation results with manually labelled ground truths to find the mismatching regions. The mismatching region is then categorized as false positive and false negative ones, respectively. Two indexes called precision and recall are adopted to measure these two types of distortions, and they are combined in F-measure to evaluate the overall segmentation quality (Shi et al., 2013).

3.0 EVALUATION OF TECHNIQUES AND ITS EFFICENCY

We have discussed several methods of segmentation so far. In this section, for the sake of completeness and illustration, we considered segmentation result produced by all several techniques discussed before. We believe that there are two key points that allow for the use of segmentation methods in a larger object detection system: correctness and stability.

Correctness is the major key ability that we desire from any method, the ability to produce results that are consistent. Thus, correctness is measured by the size of the NPR index as discussed in (Unnikrishnan et al., 2005) give the insight of the NPR. Besides that, we really should consider another important indication of a segmentation algorithm, which is stability. If an algorithm produced correct segmentation on average, but it wildly unpredictable on a randomly given image, it will be useless as a pre-processing step. We want the algorithm to produce a consistently correct segmentation of similar granularity so any processes using the algorithm can predict the output. Stability with respect to parameters and stability across the image is our primary concern. If a segmentation algorithm can be shown to be both correct and stable, then it will be useful for many future image segmentation systems.

3.1 Segmentation Results

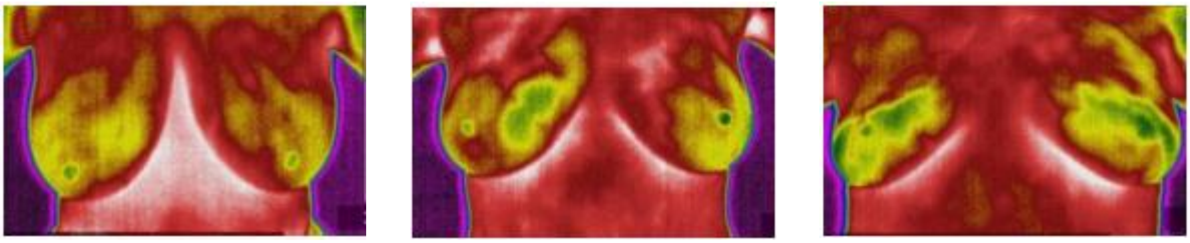
The segmentation results for some of the recent work on breast cancer image segmentation will be discussed in this section.

3.1.1 Otsu's Thresholding

Otsu's method involves iterating through all the possible threshold values and calculating measures spread for the pixel levels each side of the threshold, i.e. the pixels that fall either in foreground or in background. The objective is to find the threshold value where the sum of foreground and background spreads is at its minimum.

A bi-level and multi-level thresholding are proposed in (Raja et al., 2015) to segment cancer infected breast thermal images using Otsu's function. In the proposed image segmentation work, a histogram of the image is analysed and the optimal threshold is gathered by maximizing Otsu's between class variance function. The performance assessment is carried out using Peak Signal Noise Ratio (PSNR), Structural Similarity Index Matrix (SSIM) and CPU time. The proposed method, an Otsu guided, Particle Swarm Optimization (PSO) algorithm based multi-level thresholding had been tested on chosen RGB image data set. The simulation work is executed on a work station with Intel Core i3 2.2 Ghz CPU with 2 GB of RAM and equipped with Matlab R2010a software.

During the simulation works, the image segmentation process is repeated 10 times for each 'm' and the mean value is chosen as the optimized result. The segmentation procedure is tested on 543x345 sized Breast Thermal Images (BTI) depicted in Figure 3.



(a) Image 1 (b) Image 2 (c) Image 3

Figure 3. 543 x 345 sized breast thermal image dataset

Table 2 displays the segmented images using Improved Particle Swarm Optimization (IPSO) algorithm for m = 2 3,4,5 and the corresponding performance result for all the segmented

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images are shown in Table 3. It can be observed that the segmentation procedures enhance the cancer region compared with the original test image shown in Figure 3.

Table 2. Segmented Image Dataset using (Raja et al. 2015) work

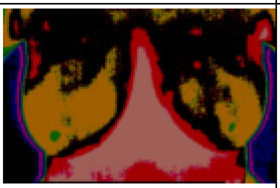
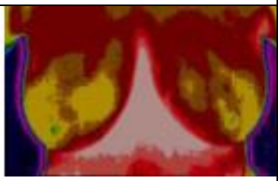
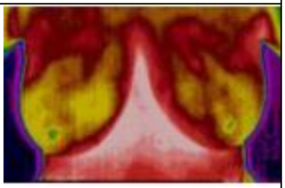
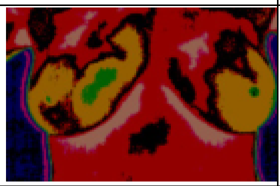
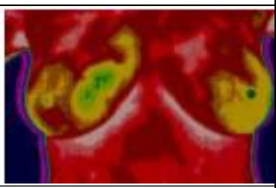
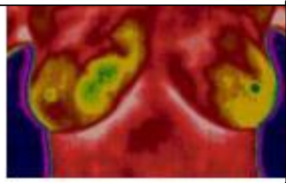
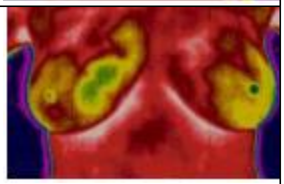
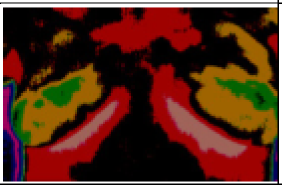
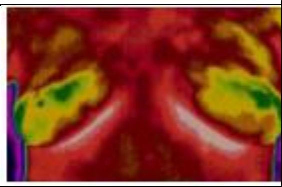
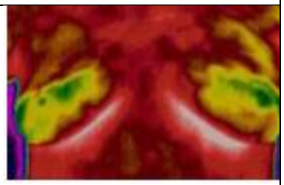
	m=2	**m=3**	**m=4**	**m=5**
Image 1				
Image 2				
Image 3				

Table 3. Performance measure obtained with IPSO algorithm when m=5 in (Raja et al. 2015)

	PSNR (dB)	**SSIM**	**CPU time (min)**
Image 1	33.01	0.770	1.392
Image 2	31.88	0.726	1.490
Image 3	29.92	0.728	1.296

3.1.2 K-Means Segmentation

Image segmentation is the procedure of separating an image into significant areas based on similarity or heterogeneity measures. In a study by Meharunnisa et al. (2015), they used K-Means clustering to associate pixels with same intensities into a set of pre-defined groups. It is based on recursive iterations and is used to partition the whole image into '*k*' clusters. The objective of K-Means is to divide a collection of regions into '*k*' group. The author finds that *k* = 5 is the best fit for all mammogram images provided in their database and this K-Means algorithm iterates mainly over 2 steps namely calculating the mean of each given k-cluster and then calculating the Euclidean measure of the distance of each data point from each

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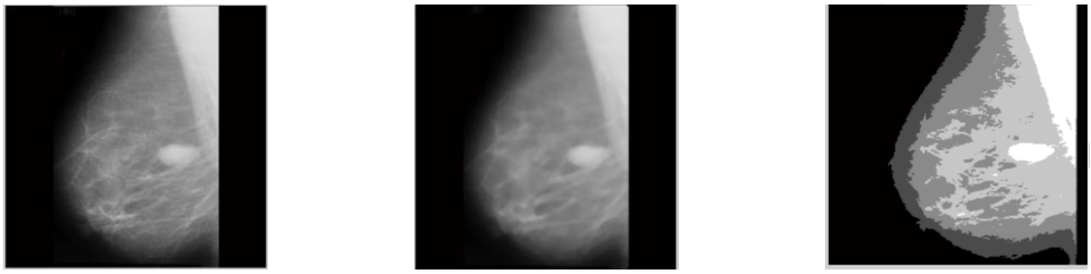
centroid of a cluster and assigning it to the nearest cluster. The preprocessed image is segmented into pre-defined 5 clusters by using K-Mean clustering method as shown in the image below.



(a) Input Image (b) Enhanced Image (c) K-Means Clustering

Figure 4. K-Means Segmentation results (Meharunnisa et al. 2015)

In the iteration course being executed, the Euclidean distance is minimized, in all the groups, which are far off the centroids from the respective data points. Figure 4 shows the output of the K-Means cluster that generally contains the cancerous mass and other regions. In an experiment conducted by Meharunnisa et al. (2015), they investigated the masses in breast cancer patients by extracting texture feature from the digital mammogram and predicting the condition of the diagnosis in this patient. The author used K-Means on the publicly available mini-MIAS mammogram database such as median filtering, CLAHE, GLCM and SVM to obtain qualitative features of the images and to classify it. The proposed algorithm obtained a score of 87.5% Sensitivity, 100% Specificity and an overall 95% Overall Accuracy. The F-Score recorded for the proposed method is 0.933 which is quite high in the research community.

K-Means Clustering is a widely used algorithm due to its simplicity and computational speed. The number of clusters ('*k*') must be known in advance. In many cases, you will have already known how many clusters the dataset contains. If so, K-Means is the perfect choice for your segmentation process. In other cases, such as the image compression in Figure 4 above, we can try K-Means with different '*k*' values and compare the results. It can be seen that K-Means is non-deterministic, so results often varies. Finally, there are certainly a set of problems where '*k*' is not known. In this case, unfortunately you will either need to find '*k*' somehow or use an entirely different algorithm.

3.1.3 Mean-Shift Segmentation

For mean shift algorithm, the first step is to represent the image as a point in space. There are many ways to accomplish this, but the easiest way is to map each pixel to a point of three-

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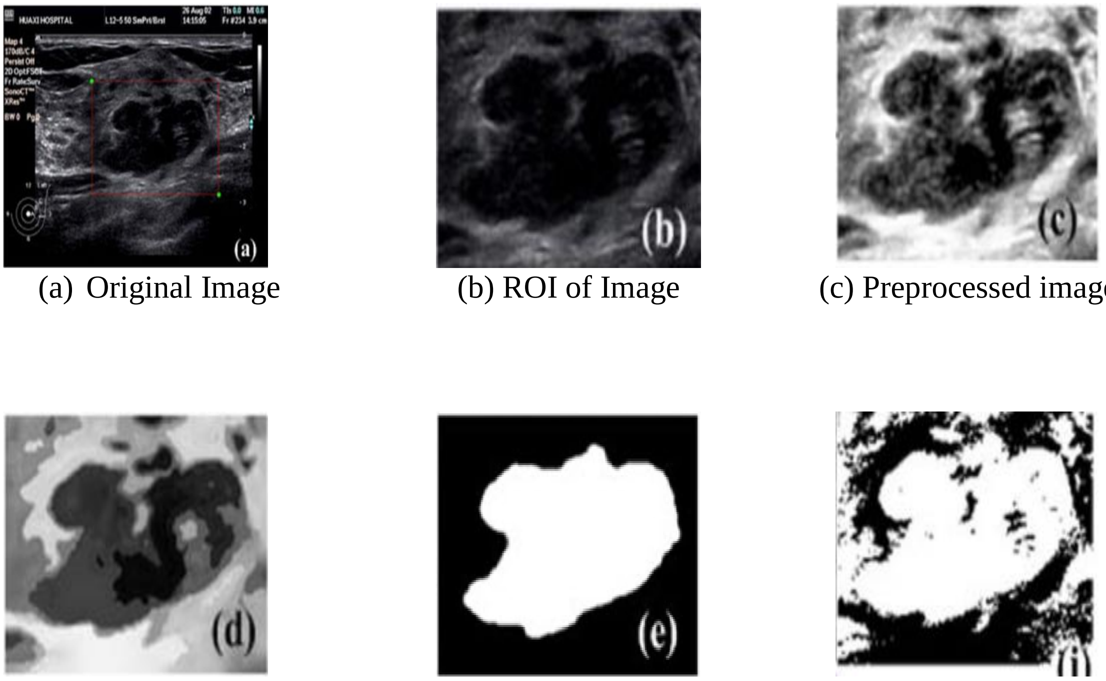
dimensional RGB space using its red, green and blue pixel values. Zhou et al. (2016) proposed a new method for semi-automatic tumour segmentation on breast ultrasound (BUS) image using Gaussian filtering, histogram equalization, Mean Shift, and graph cuts. The shrunken images were smoothed by a Gaussian filter and then contrast-enhanced by histogram equalization. Next, the enhanced image was filtered using pyramid Mean Shift to improve homogeneity. The proposed method was implemented with OpenCV 2.4.3 and Visual Studio 2010 and tested for 38 BUS images with benign tumours and 31 BUS images with malignant tumours from different ultrasound scanners.



(a) Original Image — (b) ROI of Image — (c) Preprocessed image

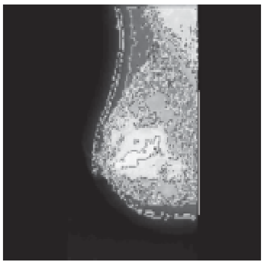
(d) Mean Shift filtered image — (e) Post processed image — (f) K-Mean segmented image, k = 2

Figure 5. Breast cancer segmentation using Mean Shift (Zhou et al., 2016)

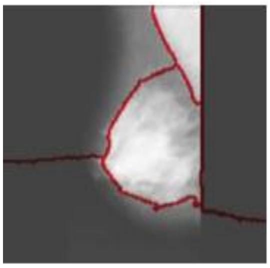
Experimental results showed that the proposed method in (Zhou et al., 2016) had a true positive rate (TP) of 91.7%, a false positive (FP) rate of 11.9%, and a similarity (SI) rate of 85.6%. The mean run time on Intel Core 2.66 GHz CPU and 4 GB RAM was 0.49 ± 0.36 s. One limitation of the proposed work is that the smoothness of the detected tumor contour is a little lower when the original boundary is noisy or blurry. Besides that, the interaction procedure of selecting the two diagonal points for Region of Interest (ROI) affects the final segmentation accuracy to some extent because the seeds for object and background are determined by the width and height of the ROI.

3.1.4 Normalized Cuts Segmentation

Image segmentation with Normalized Cuts in Figure 6 are carried out on breast masses in computer-aided mammography screening system. This study was conducted by (Liu and Zeng, 2012). After pre-processing, they extracted the texture features of the mammogram and set up the weight function, then the Normalized Cuts method is used to find the partitions of the mammogram. The mammogram images for the experiments are from the mini-MIAS database. The proposed method has shown quite promising results with high accuracy.



(a) Original mammogram image



(b) Mammogram image segmentation

Figure 6: Result of experiment for Normalized Cuts (Liu and Zeng 2012)

3.1.5 Graph-based Segmentation

Segmentation for breast tumours in ultrasound (US) images is crucial for computer-aided diagnosis system and it has always been a difficult task due to the defects inherent in the US images, such as speckles and low contrast. For references, Huang et al. (2012) proposed segmentation algorithm by constructing a graph using improved neighbourhood models. Besides that, taking advantages of local statistic, a new pair-wise region comparison predicate that is insensitive to noise was proposed to determine the emergence of any two of adjacent sub regions. The robust graph-based (RGB) which makes use of the regional statistics for determination of whether two connected sub regions could be merged is less sensitive to noises in comparison with EGB.

Figure 7 shows the segmented result using Graph-based segmentation that is proposed by Huang et al. (2012). Experimental results have shown that the proposed method could improve the segmentation accuracy by 1.5-5.6% in comparison with three often used segmentation methods, and should be capable of segmenting breast tumours in US images. The utilization of regional statistic would theoretically decrease the influence of random noises and was validated by the experimental results. Having carefully selected two

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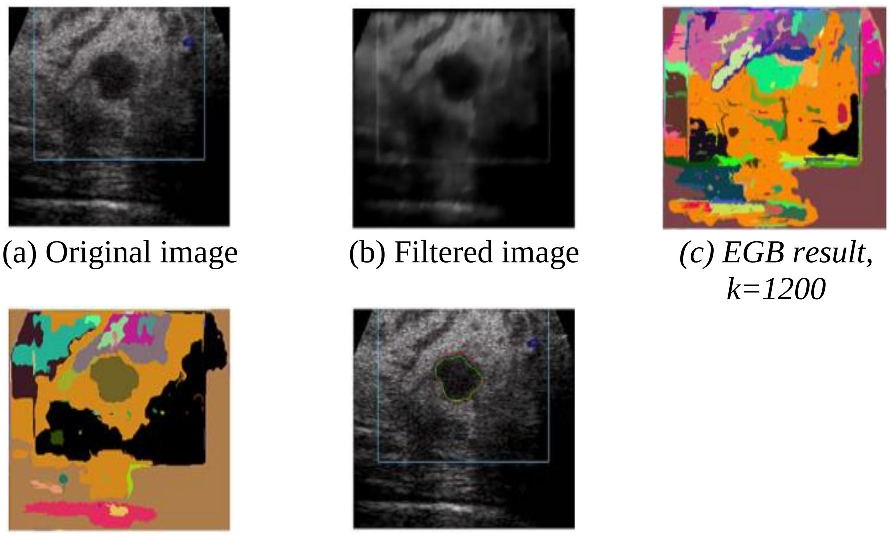
parameters *k* and α, the RGB method illustrated improved robustness to noises and better segmentation performance.

Table 4. The segmentation performance in percentage (Huang et al., 2012)

Cancer Type	Parameter of the Snake	Methods	ARE (Mean±SD)	TPVF (Mean±SD)	FPVF (Mean±SD)	FNVF (Mean±SD)
Benign	5	RGB+Snake	5.8±1.2	91.7±2.1	2.3±1.7	12.8±6.4
Malignant	5	RGB+Snake	5.7±1.1	87.4±2.1	9.8±1.6	7.5±2.1



(a) Original image (b) Filtered image *(c) EGB result, k=1200*

(d) RGB result using the 8-connected neighborhood, k=2000 (e) RGB+Snake result

Figure 7. Segmentation result using Graph-based segmentation (Huang et al. 2012)

Table 5 depicts the latest performance report for current breast cancer image segmentation.

Table 5. Current performance benchmark for breast cancer image segmentation

Method	Descriptions	Performance
Improved PSO Based Multi-level Thresholding (Raja et al., 2015)	Histogram of the image is analysed and the optimal threshold is gathered by maximizing Otsu's between class variance function	PSNR(dB) = 31.60, SSIM = 0.741, CPU Time (s) = 1.392
K-Means on the publicly available mini-MIAS (Meharunnisa et al., 2015)	Extracting texture features from digital mammograms and predicting the condition of diagnosis.	87.5% Sensitivity, 100% Specificity and an overall 95% Overall Accuracy. The F-Score recorded for the proposed method is 0.933 which is quite high in the research community.
Semi-automatic Breast Ultrasound Image Segmentation Based on Mean Shift and Graph Cuts (Zhou et al., 2016)	Semi-automatic tumour segmentation on breast ultrasound (BUS) image using Gaussian filtering, histogram equalization, Mean Shift, and graph cuts	True positive rate (TP) of 91.7%, a false positive (FP) rate of 11.9%, and a similarity (SI) rate of 85.6%. The mean run time on Intel Core 2.66 GHz CPU and 4 GB RAM was 0.49 ± 0.36 s.
Graph-based segmentation that proposed in (Huang et al., 2012)	The robust graph-based (RGB) which makes use of the regional statistics for determination of whether two connected sub regions could be merged is less sensitive to noises in comparison with efficient graph based (EGB).	ARE (Mean± SD) = 5.8±1.2, TPVF (Mean± SD) = 91.7±2.1, FPVF (Mean±SD) = 2.3±1.7. FNVF (Mean±SD) = 12.8±6.4

4.0 FUTURE RESEARCH

Image segmentations indicate the separation of images into mutually exclusive, non-overlapping, and homogeneous regions. In any medical image, segmentation is considered to be the most important and crucial process to enabling characterization, widening, and visualization of interested areas. Other future scopes can be directed to use metaheuristics algorithms based on different optimizations to optimize parameters used in different segmentation algorithms to improve their accuracy.

5.0 CONCLUSION

A few image segmentation techniques and its efficiencies have been analysed and compared in this research. Image segmentation has a promising future particularly in the medical field as the universal segmentation algorithm has become the primary focus in medical image processing. Despite many breakthrough and new discoveries, a universally accepted image segmentation method that yields more accurate result is yet to be developed as image segmentation is affected by a lot of factors namely objectives of segmented images (medical, space, marine biology and etc.), spatial characteristics of the image continuity and nature of original image itself. Nevertheless, the techniques mentioned in this paper are still sufficient for many medical image applications. These techniques can be used for object recognition and detection. However, image segmentation remains a challenging problem, specifically in medical image processing, due to the need to producing more accurate and clear images with reduced noise. Therefore, further research is needed in developing a universally accepted technique to better enhance the diagnosis of diseases and illnesses in the medical field.

REFERENCES

Bindu, Ch.Hima and K.Satya Prasad. 2012. “An Efficient Medical Image Segmentation Using Conventional OTSU Method.” 38:67–74.

Chakravarthi, Rekha, N. M. Nandhitha, S.Emalda Roslin, and N. Selvarasu. 2016. “Tumour Extraction from Breast Mammographs through Hough Transform and DNN Hybrid Segmentation Technique.” *Biomedical Research (India)* 27(4):1–6.

Crum, William R., Oscar Camara, and Derek L. G. Hill. 2006. “Generalized Overlap Measures for Evaluation and Validation in Medical Image Analysis.” *IEEE Transactions on Medical Imaging* 25(11):1451–61.

Duong, Tarn, Gaël Beck, Hanene Azzag, and Mustapha Lebbah. 2016. “Nearest Neighbour Estimators of Density Derivatives, with Application to Mean Shift Clustering.” *Pattern Recognition Letters* 80:224–30. Retrieved (http://linkinghub.elsevier.com/retrieve/pii/S0167865516301544).

Elakkia, K. and P. Narendran. 2016. "Survey of Medical Image Segmentation Using Removal of Gaussian Noise in Medical Image." 6(6):7593–95.

Felzenszwalb, Pedro F. and Daniel P. Huttenlocher. 2004. "Efficient Graph-Based Image Segmentation." *International Journal of Computer Vision* 59(2):167–81.

Huang, Qing Hua et al. 2012. "A Robust Graph-Based Segmentation Method for Breast Tumors in Ultrasound Images." *Ultrasonics* 52(2):266–75. Retrieved (http://dx.doi.org/10.1016/j.ultras.2011.08.011).

Hubert, Lawrence and Phipps Arabie. 1985. "Comparing Partitions." *Journal of Classification* 2(1):193–218.

Ifenthaler, Dirk. 2012. "Measures of Similarity." *Encyclopedia of the Sciences of Learning* 13:2147–50.

Jeyavathana, R.Beaulah, R. Balasubramanian, and A.Anbarasa Pandian. 2016. "A Survey : Analysis on Pre-Processing and Segmentation Techniques for Medical Images." III(Vi):113–20.

Kaftan, Jens N., A. Bell, Til Aach, and André A. Bell. 2008. "Mean Shift Segmentation Evaluation of Optimization Techniques." (February). Retrieved (http://www.springeronline.com/lncs).

Kanungo, Tapas et al. 2002. "An Efficient K-Means Clustering Algorithm: Analysis and Implementation." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 24(7):881–92.

Kitrungrotsakul, Titinunt, Yen Wei Chen, Xian Hua Han, and Lanfen Lin. 2015. "Supervoxels Based Graph Cut for Medical Organ Segmentation." *IFAC Proceedings Volumes (IFAC-PapersOnline)* 48(20):70–75. Retrieved (http://dx.doi.org/10.1016/j.ifacol.2015.10.117).

Li, Zhongguo, Lei Zeng, Ti Wang, Jian Chen, and Bin Yan. 2016. "Image Segmentation Based on Local Chan-Vese Model Optimized by Max-Flow Algorithm." 0–4.

Liu, Liang and Feng Zeng. 2012. "Digital Mammogram Segmentation Based on Normalized Cuts." *2012 IEEE Global High Tech Congress on Electronics, GHTCE 2012* 127–30.

Mahmood, Q., a Chodorowski, a Mehnert, and M. Persson. 2012. "A Novel Bayesian Approach to Adaptive Mean Shift Segmentation of Brain Images." *Computer-Based Medical Systems (CBMS), 2012 25th International Symposium on* 1–6.

Makkar, Himanshu. 2014. "Image Analysis Using Improved Ots U ' S Thresholding Method." 2122–26.

Meharunnisa, S. P., K. Suresh, M. Ravishankar, and Amith Bhaskar. 2015. "Detection of Breast Masses in Digital Mammograms Using SVM." 8(3):899–906.

Monica, Singh Sanjay Kumar, Agrawal Prateek, and Madaan Vishu. 2016. "Breast Cancer Diagnosis Using Digital Image Segmentation Techniques." *Indian Journal of Science and Technology* 9(28):1–5. Retrieved (http://www.indjst.org/index.php/indjst/article/view/98391).

Oliver, Arnau, Xavier Mu, and Joan Batlle. 2006. "Improving Clustering Algorithms for Image Segmentation Using Contour and Region Information." 1–6.

Padma, A. and N. Giridharan. 2016. "Performance Comparison of Texture Feature Analysis Methods Using PNN Classifier for Segmentation and Classification of Brain CT Images." *International Journal of Imaging Systems and Technology* 26(2):97–105. Retrieved (http://doi.wiley.com/10.1002/ima.22161).

Pal, N. L. and S. K. Pal. 1993. "A Review on Image Segmentation Techniques." *Pattern Recognition* 26(9):1277–94.

Pantofaru, Caroline and Martial Hebert. 2005. "A Comparison of Image Segmentation Algorithms." *Robotics* (CMU-RI-TR-05-40):123–30. Retrieved (http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.72.5443&rep=rep1&type=pdf).

Patel, Bhagwati Charan and G. R. Sinha. 2010. "An Adaptive K-Means Clustering Algorithm for Breast Image Segmentation." *International Journal of Computer Applications* 10(4):35–38. Retrieved (http://www.ijcaonline.com/volume10/number4/pxc3871982.pdf).

Powers, David M. W. 2007. "Evaluation: From Precision, Recall and F-Factor to ROC, Informedness, Markedness & Correlation." (December):24.

Raja, N.Sri Madhava, S.Arockia Sukanya, and Y. Nikita. 2015. "Improved PSO Based Multi-Level Thresholding for Cancer Infected Breast Thermal Images Using Otsu." *Procedia Computer Science* 48(Iccc):524–29. Retrieved (http://linkinghub.elsevier.com/retrieve/pii/S1877050915006390).

Rohlfing, Torsten, Robert Brandt, Randolf Menzel, and Calvin R. Maurer. 2004. "Evaluation of Atlas Selection Strategies for Atlas-Based Image Segmentation with Application to Confocal Microscopy Images of Bee Brains." *NeuroImage* 21(4):1428–42.

Saglam, A. and Baykan, N. A. 2015. "An Efficient Object Extraction with Graph-Based Image Segmentation."

Sathya, P. D. and R. Kayalvizhi. 2011. "Optimal Multilevel Thresholding Using Bacterial Foraging Algorithm." *Expert Systems with Applications* 38(12):15549–64. Retrieved (http://dx.doi.org/10.1016/j.eswa.2011.06.004).

Shi, J. and J. Malik. 2000a. "Normalized Cuts and Image Segmentation." *IEEE Trans. Pattern Anal. Machine Intell.* 22(8):888-905.

Shi, J. and J. Malik. 2000b. "Normalized Cuts and Image Segmentation." *Ieee Transactions on Pattern Analysis and Machine Intelligence* 22(8):888–905. Retrieved (http://www.computer.org/portal/web/csdl/doi?doc=abs/proceedings/cvpr/1997/7822/00/78220731abs.htm%5Cnpapers3://publication/uuid/268FC197-AF47-4C7C-887F-BEDB94A81320).

Shi, R., K. N. Ngan, and S. Li. 2013. "The Objective Evaluation of Image Object Segmentation Quality." *Acivs* 8192.

Smith, P. et al. 1979. "Smith et Al. - 1979 - A Tlreshold Selection Method from Gray-Level Histograms." 20(1):62–66.

Swetha, T. L. V. N. and Bindu, Ch. Hima. 2015. "Detection of Breast Cancer with Hybrid Image Segmentation and Otsu ' S Thresholding." *2015 Int. Conference on Computing and Network Communications*, pg. 565–70.

Suresh, Shilpa and Shyam Lal. 2016. "An Efficient Cuckoo Search Algorithm Based Multilevel Thresholding for Segmentation of Satellite Images Using Different Objective Functions." *Expert Systems with Applications* 58:184–209. Retrieved (http://linkinghub.elsevier.com/retrieve/pii/S0957417416301348).

Unnikrishnan, R., C. Pantofaru, and M. Hebert. 2005. "A Measure for Objective Evaluation of Image Segmentation Algorithms." *CVPR "05 Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR"05) - Workshops* 3:34–42. Retrieved (http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1565332).

Viola, Luciano Guivant. 2016. "Segmentation of Household Load-Profiles with K- Means Clustering Algorithm Segmentation of Household Load-Profiles with K-Means Clustering Algorithm." (July):0–9. Retrieved (https://www.researchgate.net/profile/Luciano_Viola/publication/304717810_Segmentation_of_household_load-profiles_with_K-means_clustering_algorithm/links/57786ecc08ae1b18a7e44393.pdf).

Wang, Dong, Haohan Li, Xiaoyu Wei, and Xiaoping Wang. 2016. "An Efficient Iterative Thresholding Method for Image Segmentation." 1–14. Retrieved (http://arxiv.org/abs/1608.01431).

Wang, Xiaofang, Yuxing Tang, Simon Masnou, Liming Chen, and Senior Member. 2015. "A Global / Local Affinity Graph for Image Segmentation." 24(4):1399–1411.

Yao, Hong, Qingling Duan, Daoliang Li, and Jianping Wang. 2013. "An Improved -Means Clustering Algorithm for Fish Image Segmentation." *Mathematical and Computer Modelling* 58(3–4):790–98. Retrieved (http://www.sciencedirect.com/science/article/pii/S089571771200369X).

Zhang, Rui, Hongzhi Wang, Renu Tewari, Gero Schmidt, and Deepika Kakrania. 2016. "Big

Data for Medical Image Analysis: A Performance Study." *2016 IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW)* 1660–64. Retrieved (http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7530064).

Zhang, Xiaoli, Xiongfei Li, and Yuncong Feng. 2015. "A Medical Image Segmentation Algorithm Based on Bi-Directional Region Growing." *Optik - International Journal for Light and Electron Optics* 126(20):2398–2404. Retrieved (http://www.sciencedirect.com/science/article/pii/S0030402615004830).

Zhou, Huiyu, Xuelong Li, Gerald Schaefer, M.Emre Celebi, and Paul Miller. 2013. "Mean Shift Based Gradient Vector Flow for Image Segmentation." *Computer Vision and Image Understanding* 117(9):1004–16. Retrieved (http://dx.doi.org/10.1016/j.cviu.2012.11.015).

Zhou, Huiyu, Gerald Schaefer, M.Emre Celebi, Faquan Lin, and Tangwei Liu. 2011. "Gradient Vector Flow with Mean Shift for Skin Lesion Segmentation." *Computerized Medical Imaging and Graphics : The Official Journal of the Computerized Medical Imaging Society* 35(2):121–27. Retrieved (http://www.sciencedirect.com/science/article/pii/S0895611110000820).

Zhou, Zhuhuang et al. 2016. "Semi-Automatic Breast Ultrasound Image Segmentation Based on Mean Shift and Graph Cuts." (100).