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Color Texture Segmentation using Binary Tree Cluster Quantization Technique

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ABSTRACT: Both ray tracing and point-based representations provide means to efficiently display very complex 3D models. Computational efficiency has been the main focus of previous work on ray tracing point-sampled surfaces. For very complex models efficient storage in the form of compression becomes necessary in order to avoid costly disk access. However, as ray tracing requires neighbourhood queries, existing compression schemes cannot be applied because of their sequential nature. This paper introduces a novel acceleration structure called the Quantized kd-tree, which offers both efficient traversal and storage. The gist of our new representation lies in quantizing the kd-tree splitting plane coordinates. We show that the Quantized kd-tree reduces the memory footprint up to 18 times, not compromising performance. Moreover, the technique can also be employed to provide LOD (Level-Of-Detail) to reduce aliasing problems, with little additional storage cost.

In color image processing, color pixels are traditionally treated as geometric vectors in a Euclidean color space. Typically, the three RGB color directions become the basis vectors of the color space. The quaternion representation of the color which considers a color pixel as a point in the 3D cube is used in the proposed system, since the quaternion algebra provides a very natural way to handle homogeneous coordinates.

KEYWORDS: Quantized kd-tree, color pixel, RGB Color.

I. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images [1] [2]. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection) [4]. Each of the pixels in a region is 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 characteristic(s). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes [3].

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. There is also a balanced histogram thresholding [1]. The key of this method is to select the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Recently, methods have been developed for thresholding computed tomography (CT) images [5]. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed) image. New methods suggested the usage of multi-dimensional rule-based non-linear thresholds. In these works decision over each pixel's information to a segment is based on multi-dimensional rules derived from evolutionary algorithms based on image lighting environment and application[2]

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II. RELATED WORK

Following method are the literature surveys regarding the Color Texture Segmentation.

cluster method

The K-means algorithm is an iterative technique that is used to partition an image into K clusters [2]. The basic algorithm is

1. Pick K cluster centers, either randomly or based on some heuristic
2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster centre
3. Re-compute the cluster centers by averaging all of the pixels in the cluster
4. Repeat steps 2 and 3 until convergence is attained (i.e. no pixels change clusters)

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors [5]. K can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K [1].

Compression Based Method

Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data [2]. The connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape. Each of these components is modeled by a probability distribution function and its coding length is computed as follows:

1. The boundary encoding leverages the fact that regions in natural images tend to have a smooth contour. This prior is used by Huffman coding to encode the difference chain code of the contours in an image. Thus, the smoother a boundary is, the shorter coding length it attains [1].
2. Texture is encoded by lossy compression in a way similar to minimum description length (MDL) principle, but here the length of the data given the model is approximated by the number of samples times the entropy of the model. The texture in each region is modelled by a multivariate normal distribution whose entropy has closed form expression. An interesting property of this model is that the estimated entropy bounds the true entropy of the data from above. This is because among all distributions with a given mean and covariance, normal distribution has the largest entropy. Thus, the true coding length cannot be more than what the algorithm tries to minimize [3].

For any given segmentation of an image, this scheme yields the number of bits required to encode that image based on the given segmentation. Thus, among all possible segmentations of an image, the goal is to find the segmentation which produces the shortest coding length. This can be achieved by a simple agglomerative clustering method. The distortion in the lossy compression determines the coarseness of the segmentation and its optimal value may differ for each image [6]. This parameter can be estimated heuristically from the contrast of textures in an image. For example, when the textures in an image are similar, such as in camouflage images, stronger sensitivity and thus lower quantization is required.

Histogram- Based Method

Histogram-based methods are very efficient compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure. A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters [7]. This operation is repeated with smaller and smaller clusters until no more clusters are formed.

One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image. Histogram-based approaches can also be quickly adapted to apply to multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and

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valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per-pixel basis where the resulting information is used to determine the most frequent color for the pixel location [6]. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in Video tracking.

III. EDGE DETECTION

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries. The desired edges are the boundaries between such objects or spatial-taxons.

Spatial-taxons are information granules, consisting of a crisp pixel region, stationed at abstraction levels within hierarchical nested scene architecture. They are similar to the Gestalt psychological designation of figure-ground, but are extended to include foreground, object groups, objects and salient object parts. Edge detection methods can be applied to the spatial-taxon region, in the same manner they would be applied to a silhouette. This method is particularly useful when the disconnected edge is part of an illusory contour.

Segmentation methods can also be applied to edges obtained from edge detectors. Lindeberg and Li developed an integrated method that segments edges into straight and curved edge segments for parts-based object recognition, based on a minimum description length (M_{DL}) criterion that was optimized by a split-and-merge-like method with candidate breakpoints obtained from complementary junction cues to obtain more likely points at which to consider partitions into different segments [3].

IV. DUAL CLUSTERING METHOD

This method is a combination of three characteristics of the image: partition of the image based on histogram analysis is checked by high compactness of the clusters (objects), and high gradients of their borders. For that purpose two spaces has to be introduced: one space is the one-dimensional histogram of brightness H = H (B), the second space – the dual 3-dimensional space of the original image itself B = B(x, y). The first space allows to measure how compact is distributed the brightness of the image by calculating minimal clustering kmin. Threshold brightness T corresponding to kmin defines the binary (black-and-white) image – bitmap $b = \varphi(x, y)$, where $\varphi(x, y) = 0$, if $B(x, y) < T$, and $\varphi(x, y) = 1$, if $B(x, y) \geq T$. The bitmap b is an object in dual space. On that bitmap a measure has to be defined reflecting how compact distributed black (or white) pixels are. So, the goal is to find objects with good borders. For all T the measure $M_{DC} = G/(k-L)$ has to be calculated (where k is difference in brightness between the object and the background, L is length of all borders, and G is mean gradient on the borders)[6]. Maximum of MDC defines the segmentation

V. MODEL BASED SEGMENTATION

The central assumption of such an approach is that structures of interest/organs have a repetitive form of geometry. Therefore, one can seek for a probabilistic model towards explaining the variation of the shape of the organ and then when segmenting an image impose constraints using this model as prior. Such a task involves (i) registration of the training examples to a common pose, (ii) probabilistic representation of the variation of the registered samples, and (iii) statistical inference between the model and the image. State of the art methods in the literature for knowledge-based segmentation involve active shape and appearance models, active contours and deformable templates and level-set based methods [5].

A. Multi-scale Segmentation

Image segmentations are computed at multiple scales in scale space and sometimes propagated from coarse to fine scales; see scale-space segmentation. Segmentation criteria can be arbitrarily complex and may take into account global as well as local criteria. A common requirement is that each region must be connected in some sense.

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B. One-dimensional hierarchical signal segmentation

Witkin's seminal working scale space included the notion that a one-dimensional signal could be unambiguously segmented into regions, with one scale parameter controlling the scale of segmentation.

A key observation is that the zero-crossings of the second derivatives (minima and maxima of the first derivative or slope) of multi-scale-smoothed versions of a signal form a nesting tree, which defines hierarchical relations between segments at different scales. Specifically, slope extreme at coarse scales can be traced back to corresponding features at fine scales. When a slope maximum and slope minimum annihilate each other at a larger scale, the three segments that they separated merge into one segment, thus defining the hierarchy of segments.

C. Image segmentation and primal sketch

There have been numerous research works in this area, out of which a few have now reached a state where they can be applied either with interactive manual intervention (usually with application to medical imaging) or fully automatically. The following is a brief overview of some of the main research ideas that current approaches are based upon.

The nesting structure that within described is, however, specific for one-dimensional signals and does not trivially transfer to higher-dimensional images. Nevertheless, this general idea has inspired several other authors to investigate coarse-to-fine schemes for image segmentation. Koenderink proposed to study how iso-intensity contours evolve over scales and this approach was investigated in more detail by Lifshitz and Pizer [7]. Unfortunately, however, the intensity of image features changes over scales, which implies that it is hard to trace coarse-scale image features to finer scales using iso-intensity information.

Lindeberg studied the problem of linking local extreme and saddle points over scales, and proposed an image representation called the scale-space primal sketch which makes explicit the relations between structures at different scales, and also makes explicit which image features are stable over large ranges of scale including locally appropriate scales for those. Bergholm proposed to detect edges at coarse scales in scale-space and then trace them back to finer scales with manual choice of both the coarse detection scale and the fine localization scale [6].

Gauch and Pizerstudied the complementary problem of ridges and valleys at multiple scales and developed a tool for interactive image segmentation based on multi-scale watersheds. The use of multi-scale watershed with application to the gradient map has also been investigated by Olsen and Nielsen and been carried over to clinical use by Dam Vincken et al. proposed a hyper stack for defining probabilistic relations between image structures at different scales. The use of stable image structures over scales has been furthered by Ahuja and his co-workers into a fully automated system. A fully automatic brain segmentation algorithm based on closely related ideas of multi-scale watersheds has been presented by Undeman and Lindeberg and been extensively tested in brain databases. These ideas for multi-scale image segmentation by linking image structures over scales have also been picked up by Florack and Kuijper. Bijaoui and Ruéassociate structures detected in scale-space above a minimum noise threshold into an object tree which spans multiple scales and corresponds to a kind of feature in the original signal. Extracted features are accurately reconstructed using an iterative conjugate gradient matrix method.

D. Semi-automatic segmentation

In one kind of segmentation, the user outlines the region of interest with the mouse clicks and algorithms are applied so that the path that best fits the edge of the image is shown.

Techniques like SIOX, Livewire, Intelligent Scissors or IT-SNAPS are used in this kind of segmentation. In an alternative kind of semi-automatic segmentation, the algorithms return a spatial-taxon (i.e. foreground, object-group, object or object-part) selected by the user or designated via prior probabilities.

E. Trainable segmentation

Most segmentation methods are based only on color information of pixels in the image. Humans use much more knowledge than this when doing image segmentation, but implementing this knowledge would cost considerable computation time and would require a huge domain-knowledge database, which is currently not available. In addition to traditional segmentation methods, there are trainable segmentation methods which can model some of this knowledge.

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Neural Network segmentation relies on processing small areas of an image using an artificial neural network or a set of neural networks. After such processing the decision-making mechanism marks the areas of an image accordingly to the category recognized by the neural network. A type of network designed especially for this is the Kohonen map. Pulse-coupled neural networks (PCNNs) are neural models proposed by modeling a cat's visual cortex and developed for high-performance biomimetic image processing. In 1989, Eckhorn introduced a neural model to emulate the mechanism of a cat's visual cortex. The Eckhorn model provided a simple and effective tool for studying the visual cortex of small mammals, and was soon recognized as having significant application potential in image processing. In 1994, the Eckhorn model was adapted to be an image processing algorithm by Johnson, who termed this algorithm Pulse-Coupled Neural Network. Over the past decade, PCNNs have been utilized for a variety of image processing applications, including: image segmentation, feature generation, face extraction, motion detection, region growing, noise reduction, and so on. A PCNN is a two-dimensional neural network. Each neuron in the network corresponds to one pixel in an input image, receiving its corresponding pixel's color information (e.g. intensity) as an external stimulus. Each neuron also connects with its neighboring neurons, receiving local stimuli from them. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. Through iterative computation, PCNN neurons produce temporal series of pulse outputs. The temporal series of pulse outputs contain information of input images and can be utilized for various image processing applications, such as image segmentation and feature generation. Compared with conventional image processing means, PCNNs have several significant merits, including robustness against noise, independence of geometric variations in input patterns, capability of bridging minor intensity variations in input patterns

VI. COLOR TEXTURE SEGMENTATION USING IMPROVED QUATERNION –JSEG

Binary quaternion moment-preserving (BQMP) thresholding technique and level set functions are used for the reduction of color space dimensionality. BQMP thresholding technique considers the spectral bands collectively i.e. a pixel of a given color image is considered as a point in a 3D cube. The authors Pei and Cheng (1999) have designed quaternion moment based operators using BQMP thresholding for the applications of color image processing such as color image compression, multi-class clustering of color data, and sub pixel color edge detection. They have also proved that the classification results of BQMP thresholding technique which is a two class classifier is close to that of the optimum Bayes classifier for normal-distribution datasets. Histogram equalization is performed in the proposed system in order to acquire normal distribution color dataset.

The proposed method follows the idea of Sudirman and Qiu (2000). But instead of splitting the polygon by a line iteratively and storing the local information in a file, the proposed method constructs the level set function (Kass et al 1987) and updates the level set function from the binary image obtained by BQMP thresholding technique using Heaviside function in order to reduce the computational complexity. That is the computationally intensive polygon splitting process is totally removed and the entire binary image is updated as partitions in the level set functions. Simple arithmetic operations are used to update the level set functions to speed up the computational process. Number of levels in the binary tree obtained by the proposed method and the number of final clusters are very much reduced since the binary image itself is considered as partitions. Finally, it builds a color map with smaller subset of colors that minimizes overall distortion [2].

The quantized image obtained using this new color quantization method is applied in JSEG (J measure based segmentation) algorithm (Deng et al 2001). In JSEG, a spatial segmentation algorithm was employed on a quantized class map, which was computed by a non linear filtering algorithm.

In the spatial segmentation, J-image which represents the region interiors and region boundaries was calculated using a homogeneity measure J. Then an arbitrary class region growing and region merging algorithm (Tremeau 1997, Deng et al 2001) was performed using the J-image to segment the image. JSEG is one of the popular and simple segmentation algorithms, which was attracted by many researchers. Since the author of JSEG openly admit the drawbacks of JSEG and provide ideas for future enhancement, several modifications and comparisons were done with JSEG in the last decade. JSEG consists of two stages, quantization stage and spatial segmentation stage. Zheng et al (2004) and Wang et al (2004) enhanced JSEGfrom the aspect of the result of color quantization. Jing et al (2003) modified JSEG by introducing H measure in its spatial segmentation stage and named their algorithm HSEG [6].

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A. The proposed color quantization method

In color image processing, color pixels are traditionally treated as geometric vectors in a Euclidean color space. Typically, the three RGB color directions become the basis vectors of the color space. The quaternion representation of the color which considers a color pixel as a point in the 3D cube is used in the proposed system, since the quaternion algebra provides a very natural way to handle homogeneous coordinates.

The significant requirement of this quantization procedure is the color pixels should be uniformly distributed in the RGB cube. But the R, G and B components in the RGB space involving natural images are highly correlated. The RGB color space also suffers from non-uniformity, hard visualization, since the full range of perceptible color by humans is not available by the RGB color mode. Hence it is difficult to evaluate the perceived differences between colors on the basis of distances. To alleviate this problem histogram equalization technique is applied on the original RGB image.

B. Level-set Implementation of Multiclass Clustering Algorithm using BQMP Thresholding Technique

In the quaternion representation, a pixel in the color image is represented by a hyper-complex form as

$ijk = i^2 = j^2 = k^2 = -1$

$Q = Q_0 + Q_1 i + Q_2 j + Q_3 k$

The hyper complex operators i, j, and k follow the rule

An RGB color pixel can be shown as a quaternion with Q_o=0, Q_1=R, Q2=G and Q_3 =B .The BQMP thresholding technique in a quaternion- valued pixel-set selects a hyper plane as a threshold, and assigns all the below-threshold pixels to class I (1 C)and above-threshold pixels to class II (2 C) and acts as a two class classifier. This process is repeated iteratively on each class till the predetermined number of clusters (k) is reached. The variance of the class can also be considered as stopping criteria for this iterative process.

The proposed quantization method considers the variance of the class as stopping criteria. The threshold is fixed for the variance of the class, which depends on the property of the given image. In this paper, the threshold for the variance of the class is set to 1/30 of the variance of the original image and the number of color divisions performed in the quantization process is considered as the second stopping criteria. The three important components of the quantization procedure are binary tree formation, level set formulation and level set implementation. The following subsections explain these components.

C. Binary Tree formation

The proposed method follows a divisive clustering procedure that generates a binary tree. Divisive methods are inspired by the divide-and conquer approach. Divide-and-conquer approach works for the problems, which can be recursively divided into smaller sub-problems, which are similar to the original problem. Solving the sub-problems and combining the solutions gives the solution to the original problem. Divisive methods start with the original image which is the root node. The original image is then divided into two partitions. Old node of split partition is discarded and two new nodes are formed as the regions of the two new partitions. Process of division continues until the predefined number of leaf nodes M is reached or the variances of all the partitions are lesser than the threshold.

Divisive algorithms follow simple concepts, but involve more details. Main question is how to select the node for splitting and how to split. First, algorithm needs to decide, which partition to split. The proposed method follows the BFS order to select the node for partitioning. But the node

is split table or not is decided by the number of pixels, variance of the node and the threshold. In the proposed approach BQMP thresholding technique is used to split the node. The node regions and the partitions are represented by the primary and secondary level set functions which are explained in the following subsections. During every division the cluster membership (or node number) should be assigned to each pixel. This assignment considers the membership of its parent. The node membership queue consists of this membership information, which is used to extract the node region from the primary level set function.

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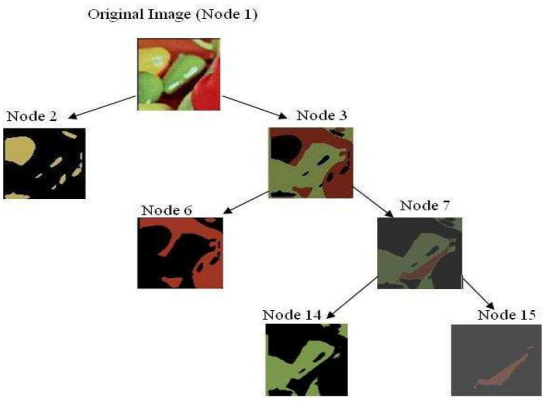

Figure 1 Hierarchical binary tree formed during the color quantization of the pepper image using the proposed algorithm

D. Parameter

K= Maximum possible clusters required.
C= A cell array containing cluster structures.
Each cluster has Following Field:
Point = an integer array containing linear indices of points in clusters.
M = Sum of RGB values of all the pixels in cluster
N= Number of Pixels in the cluster
R= the sum of squares of pixels in the cluster

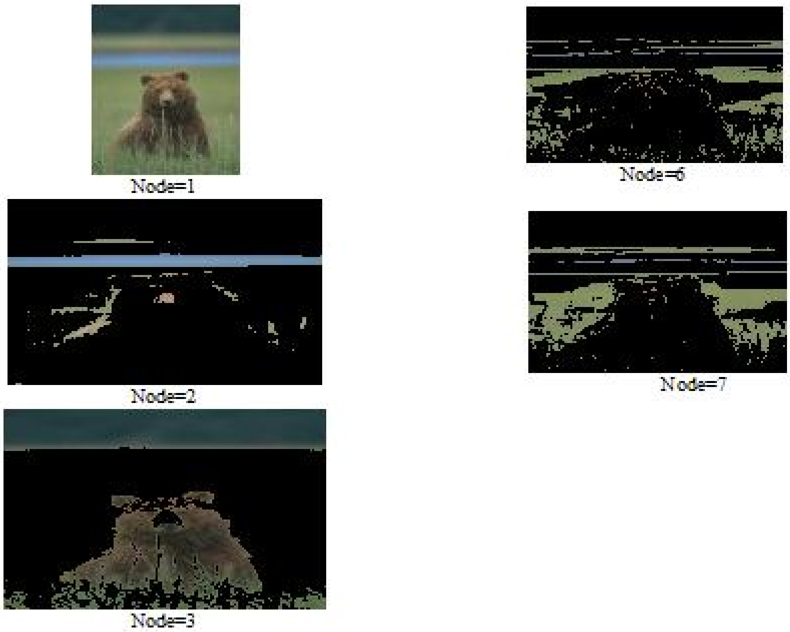

Figure 2: Simulation result for node 1,2,3,6 and 7

Figure 2 shows the hierarchical binary tree structure of the pepper image generated by the proposed method and the membership values assigned to each node for simulation result. The original image is considered as node 1 and its children are numbered as node 2 and node 3. In general, nth node's left child and right child are numbered as 2n and 2n+1 respectively. The leaf nodes are considered as clusters. Node 6, 7, is the clusters formed by the proposed clustering. The next subsection explains the level set formulation employed in the proposed multiclass clustering approach

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VII. RESULT AND CONCLUSION

A new quantization method which uses projective geometry and level set methods is developed for JSEG color texture segmentation. The new color quantization method is a divisive clustering method that employs binary quaternion moment preserving thresholding technique that considers both the spectral and spatial homogeneity of the colors, for dividing the color clusters in the RGB cube. Histogram equalization was performed to normally scatter the colors in the RGB cube and improve the color contrast of the image.

The proposed method generates a binary tree where each node represents the partitions. The nodes are logical and no physical memory is allocated for the internal nodes. Only the leaf nodes contain the quantized color information. Node information and partitioning information are stored in the level-set functions. This reduces the memory space and time complexity of the proposed divisive clustering algorithm. The pros and cons of JSEG segmentation are discussed and the new color quantization algorithm is applied to improve the performance better than JSEG. A pragmatic sky correction algorithm and new region merging technique based on Bhattacharya distance are introduced in JSEG and the proposed segmentation method is named Q-JSEG, since it uses a quaternion based color quantization approach. The number of clusters in a given color image is automatically determined by computing an excellence factor based on within-cluster and between cluster measures.

REFERENCES

[1] A. Bouman and M. Shapiro (2002): "A multiscale Random field model for Bayesian image segmentation", IEEE Transactions on Image Processing, pp. 162-177, Vol. 3

[2] Barghout, Lauren, and Lawrence W. Lee. "Perceptual information processing system." Paravue Inc. U.S. Patent Application 10/618,543, filed July 11, 2003

[3] Forghani, M.; Forouzanfar, M.; Teshnehlab, M. (2010). "Parameter optimization of improved fuzzy c-means clustering algorithm for brain MR image segmentation".Engineering Applications of Artificial Intelligence **23** (2): 160–168.

[4] W. Wu, A. Y. C. Chen, L. Zhao and J. J. Corso (2014): "Brain Tumor detection and segmentation in a CRF framework with pixel-pairwise affinity and super pixel-level features", International Journal of Computer Aided Radiology and Surgery, pp. 241-253, Vol. 9

[5] E. B. George and M. Karnan (2012): "MR Brain image segmentation using Bacteria Foraging Optimization Algorithm", International Journal of Engineering and Technology, Vol. 4.

[6] J. A. Delmerico, P. David and J. J. Corso (2011): "Building façade detection, segmentation and parameter estimation for mobile robot localization and guidance", International Conference on Intelligent Robots and Systems, pp. 1632-1639

[7] Batenburg, K J.; Sijbers, J. "Adaptive thresholding of tomograms by projection distance minimization". Pattern Recognition **42** (10): 2297–2305.doi:10.1016/j.patcog.2008.11.027

[8] en.wikipedia.org/wiki/MATLAB