IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Volume-5, Issue-1 E-ISSN: 2347-2693

Wavelet approximated texture data watershed transform (WATDWT) segmentation of Bio-Medical Images

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Available online at: www.ijcseonline.org

Received:25/12/2016 Revised: 08/01/2017 Accepted: 22/01/2017 Published: 31/01/2017

***Abstract*—Extraction of features from the biomedical image using the texture and color space based image processing analysis algorithm is developed using hybrid of DWT, entropy filtering and watershed transform is discussed in this article. To extract the textures we have used entropy features using function on the MATLAB algorithm where it corresponds to the input image parameter with the use of spatial based parameters. The texture analysis based skin texture extraction algorithm consists of steps related to decomposing the input image into a set of binary images from which the color space dimensions of the resulting regions can be computed in order to describe segmented texture patterns.**

Keywords- Image segmentation, Image texture analysis, Image watershed transform, Image dwt2

I. INTRODUCTION

The Image segmentation is one of the most fundamental and difficult problems in image analysis. Image segmentation is an important part in image processing. In computer vision, image segmentation is the process of partitioning an image into meaningful regions or objects. There are various applications of image segmentation like locate tumours or other pathologies, measure tissue volume, computer-guided surgery, treatment planning, study of anatomical structure, locate objects in satellite images and fingerprint recognition etc. Segmentation subdivides an image into its constituent region or object. Image segmentation methods are categorized on the basis of two properties discontinuity and similarity [1]. Based on this property image segmentation is categorized as Edged based segmentation and region based segmentation. The segmentation methods that are based on discontinuity property of pixels are considered as boundary or edges based techniques. Edge based segmentation method attempts to resolve image segmentation by detecting the edges or pixels between different regions that have rapid transition in intensity and are extracted and linked to form closed object boundaries. The result is a binary image. Based on theory there are two main edge based segmentation methods, gray histogram based and gradient based method [2]. Region based segmentation partitions an image into regions that are similar according to a set of predefined criteria. The region based segmentation is partitioning of an image into similar areas of connected pixels. Each of the pixels in a region is similar with respect to some characteristic or computed property such as colour, intensity and/or texture. Methods like thresholding, region growing and region splitting and merging [2]. Thresholding is an important technique in image segmentation applications. The basic idea of thresholding is to select an optimal gray-level threshold value for separating objects of interest in an image from the background based on their gray-level distribution. While humans can easily differentiable an object from complex background and image thresholding is a difficult task to separate them. The gray-level histogram of an image is usually considered as efficient tools for development of image thresholding algorithms. Thresholding creates binary images from grey-level ones by turning all pixels below some threshold to zero and all pixels about that threshold to one.

Modern medical diagnosis utilizes techniques of visualization of human internal organs (CT, MRI) or of its metabolism (PET). However, evaluation of acquired images made by human expert is usually subjective and qualitative only. Quantitative analysis of MR data, including tissue classification and segmentation, is necessary to perform e.g. attenuation compensation, motion detection, and correction of partial volume effect in PET images, acquired with PET/MR scanners. This present a software, which supports 2D and 3D medical image analysis aiming at quantification of image texture. Implements procedures for evaluation, selection and extraction of highly discriminative texture attributes combined with various classification, visualization and segmentation. Texture, as perceived by humans, is a visualization of complex patterns composed of spatially organized, repeated sub-patterns, which have a characteristic, somehow uniform appearance [2]. The local sub-patterns

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within an image demonstrate specific brightness, colour size, roughness, directivity, randomness, smoothness, granulation, etc. A texture may carry substantial information about the structure of physical objects – consequently, textural image analysis is an important issue in image processing and understanding. Especially, texture plays an important role in biomedical images, where it characterizes internal structure of tissues and organs. Texture is present in vast majority of such images acquired by different modalities, including PET, MRI, CT, echocardiography, etc. Humans usually assess the texture only qualitatively, while often its quantitative analysis is required to obtain objective and reliable diagnostic information. It was already utilized in many areas including MRI measurement protocol optimization [2] and various medical studies, to mention just the latest [3,4,5]. There are not many software tools for quantitative image texture available.

II. RELATED WORK

The use of anatomical atlases as reference pictures to advisor segmentation of new graphics could be very popular in exceptional clinical applications, e.G., for segmenting mind and its internal structures or segmenting pathological lungs, lung lobes, coronary heart and aorta, and inner belly organs [6]. The atlas customarily depicts prototypical areas and shapes of anatomical buildings along side their spatial relations [6]. All of the identified atlas-established methods will also be labeled into single and multi atlas-established segmentation.

Single atlas-centered segmentation uses an atlas built from one or more labelled segmented photos. As soon as the atlas is created, it's registered to the goal image, and the intention vicinity map is obtained by using so called label propagation that transfers the labels from the atlas again to the image using the same geometric mapping as the registration. Obviously, the segmentation accuracy depends on the registration (if the latter fails, so does the segmentation). The registration continuously involves time ingesting and tricky local deformations. Additionally, the segmentation is suffering from the capacity of the atlas to symbolize the entire population of snap shots into consideration.

A single photograph to construct the atlas can be selected randomly, or through visible inspection based on sensible criteria, or made artificially [7]. If the atlas is built from a few images, one image can also be selected as a reference and all different snap shots are registered to it. To broaden the signal-to-noise ratio, the entire registered pics are averaged, and the segmented common picture is used as the atlas [8]. However, the atlas can also be built with the aid of reworking the reference to the typical snapshot and segmenting the transformed reference [9]. Probabilistic atlases built through averaging the modified images and inspecting the corresponding labels [10] furnish special weights of each and every pixel. Nevertheless, an usual atlas does not handle elastic deformations of internal structures for the duration of the registration process. To beat this difficulty, Leemput [11] proposed a mesh-centered atlas illustration instead of the average atlas. Also, an iterative atlas iteration makes use of the output of each generation as the enter of the following iteration [6].

Multi atlas-headquartered segmentation registers many independently developed atlases to a target image after which combines their segmentation labels. The underlying concept is that fusion of multiple independent classifiers might produce higher classification [12]. There exist distinct approaches for segmenting a precise goal photo, e.G., to opt for all the atlases or simplest their subset as well as to pick one or one other approach of mixing the selected atlases to provide the purpose vicinity map. The pre or post registration determination of atlases can be centered on specified matching standards such because the mutual knowledge or the degree of deformation of the article of curiosity (undoubtedly, the atlases of the absolute best nearby mutual information or the least object deformation are top-rated).

Standard methods of mixing the selected atlases to section the target image include selection fusion (often known as majority balloting, majority rule, or label balloting). On this procedure, the label of each pixel or voxel is chosen because the label that many of the segmentations agree on [13]. Yet another technique, known as simultaneous actuality and performance level estimation (STAPLE), evaluates the efficiency of every classifier iteratively, weighs the corresponding segmentation for this reason, and uses the EM technique to find the great ultimate segmentation [14]. Isgum et al. [7] combined the propagated labels with the aid of spatially variant decision fusion weights derived from the nearby comparison of the registration accuracy, and Rohlfing and Maurer [15] proposed a shape-centered averaging process based on the Euclidean distance map to perform the combining.

III. METHODOLOGY

Osteoarthritis is considered to be one of the leading causes of disability today. It is a degenerative disease that affects the entire joint, degrading articular cartilage and deforming the surrounding bones and tissue of the affected joint. The disease is associated with pain, disability and substantial care costs each year. Experienced clinicians currently perform the clinical grading of x-ray images. However, the features involved in OA are continuous, so the classification into the distinctive grades (normal, doubtful, minimal, moderate and severe) is often left to the subjective opinion of the grader. This quantisation and the uncertainties in assigning a grade make it hard to detect changes. Clinical trials thus require large numbers of subjects to identify effects of interventions reliably. There is a need for automated methods to make measurements and classifications to remove subjectivity.

Work in the area of OA classification on radiographs is still limited.
The most significant approaches are analysing textural information across the joint using image processing techniques. These methods look at the texture across the overall joint, with implicit shape information gathered from the radiographic images. However, from the patho-physiological properties of the progression of the disease, it is apparent that both shape and texture are useful for describing OA.
The objective of work is to perform cardiac image segmentation by partitioning them into disjoint clusters with equivalent performance of human perception of the region of interest. It will be a unsupervised segmentation of cardiac organs scanned images which accomplish the requirement of making prior assumptions about the ROI. We will apply a two-stage method for such images segmentation will be performed that can process both textured and non-textured.
First stage calculates textured features from the bands coefficients of the dual-tree wavelet transform of image. Thereafter median filtering will be applied to minimize the ambiguities of texture regions at the boundaries of the image objects.
The calculated texture feature will be used to find the space based gradient function and then watershed transform will be applied to obtain the initial segmentation.
The second stage the segmented regions obtained by watershed transform are grouped to meaningful region of similar features by using spectral clustering technique by using the weighted mean based cost function for region partitioning.

Algorithm

(1) Image acquisition: Read the biomedical image (I) and perform image resizing and select region of interest that is to be cropped.

(2) 1 level Image DWT: Perform the first level 2d DWT on the image and obtain the approximation component (A) of the transformed data.

[A DH DV DD]= DWT (I)

(3) 2 level Image DWT: Perform the second level 2d DWT on the image and obtain the next approximation component (A1) of the transformed data.

[A1 DH1 DV1 DD1]= DWT(A)

(4) Approximated Image Reconstruction by 2level IDWT: Perform inverse DWT and reconstruct the image by considering only approx component and suppressing the DH, DV and DD detailed component.

(5) Entropy filtering: Apply entropy filtering to reconstruct approximated image.

(6) Remove small objects: Remove the unwanted openings having size less than 100 pixels.

(7) Morphological Processing: Apply image closing and filling operations to eliminate noise in the filtered image.

(8) Texture Masking: Mask the texture 1 and texture 2 to develop texture based segmented image.

(9) Edge Detection: Apply sobel filtering for highlighting the edge boundaries and then determine the gradient magnitude to get image having one at boundaries otherwise zero for inner regions.

(10) Edge Erosion: Apply erosion of object less than dist size 4 pixel and perform reconstruction.

(11) Edge Dilation: Apply dilation of object less than disk size 4 pixel and perform reconstruction.

(12) Thresholding: Apply the threshold on edge objects to select the segmented boundaries to high intensity.

(13) Watershed Transform: Apply watershed transform on the image obtained after segmentation.

(14) Superimposing of segmented image: Superimpose texture based segments image over the watershed transform applied segmented image by alpha blending.

IV. RESULT AND DISCUSSION

This section presents application results of biomedical image segmentation analyses using the proposed Wavelet approximated texture data watershed transform (WATDWT) segmentation. The figure 1 shows the image of human stomach side view MR cross-sections, containing liver, pancreas and spinal bones. This image (figure 1(a)) is used for visualizing WATDWT segmentation of these organs images segmentation for the aim of detection and discrimination of glands and bones from other tissues and image background. The extracted region is interpreted by physicians to evaluate bone micro architecture in osteoporosis diagnosis. The WATDWT segmentation model was applied to evaluate texture features (figure 1(b)). Segmentation results of the image in figure 1(b) are passed through watershed transforms to obtain segmented colours for different regions 1(c). Finally the coloured segments of water shed transform are superimposed with texture based segmented image(figure 1(d)).

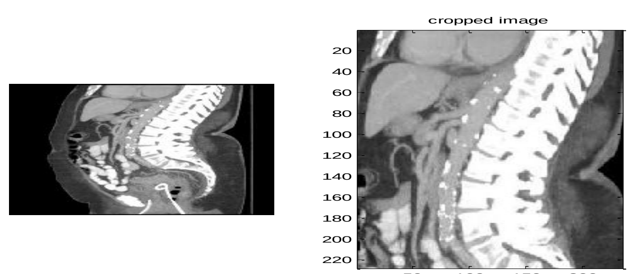

Figure 1(a): Original image (left) cropped image for region of interest (right)

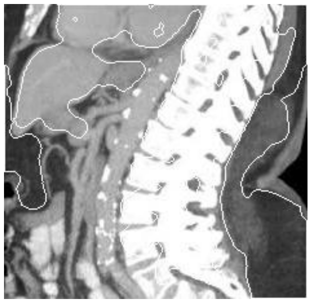

Figure 1(b): Texture based segmented image

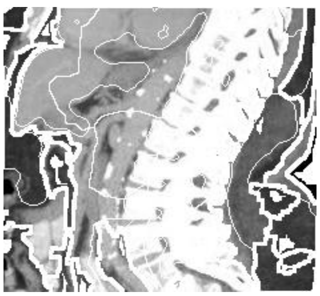

Figure 1(c) Coloured watershed label matrix

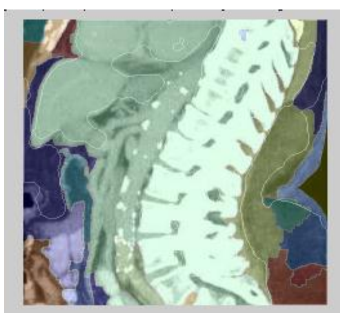

Figure 1(d) Superimposed image of figure 1(b) and (c).

Results are also analyzed for the brain MRI and organ cross sections shown in figure 2 and 3.

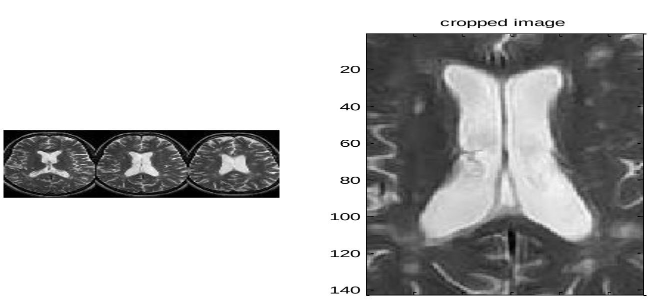

Figure 2(a): Original image (left) Cropped image for region of interest (right)

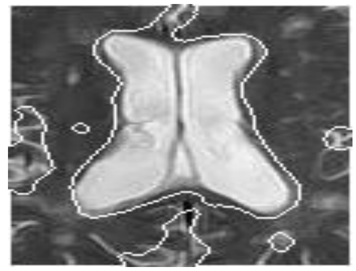

Figure 2(b): Texture based segmented image

Figure 2(c) Segmented image after applying watershed transform on figure 2(b) image.

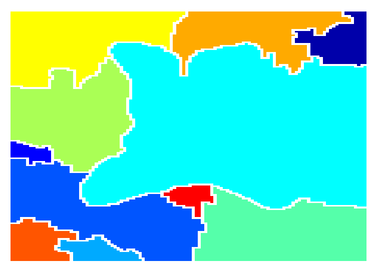

Figure 2(d) Coloured Watershed label matrix

Figure 2(e) Superimposed image of figure 2(c) and (d).

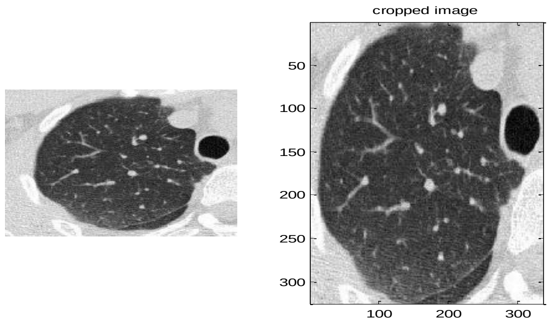

Figure 3(a) :Original image (left) Cropped image for region of interest (right)

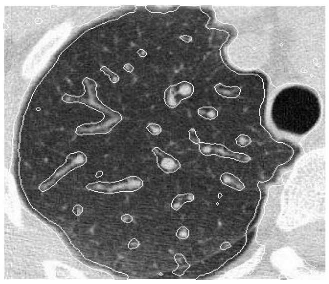

Figure 3(b) Texture based segmented image

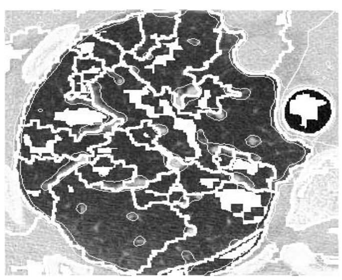

Figure 3(c) Segmented image after applying watershed transform on figure 3(b) image.

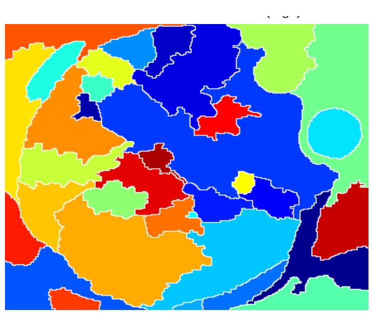

Figure 3(d) Colored watershed label matrix

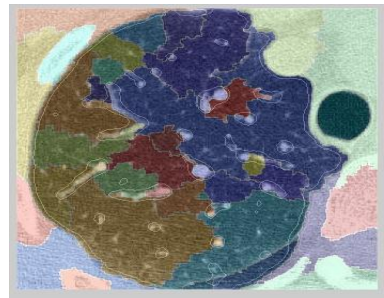

Figure 3(e) Superimposed image of figure 3(c) and (d).

V. CONCLUSION

Texture and coarseness of organs are visually different. On applying image processing in the segmentation analysis it is found helpful to quantitatively evaluate differences texture features when applied on wavelet approximated component. In this work, we have used a texture analysis and measurements based on segmentation based approach of the texture recognition. The texture is the appearance of the smooth surface. To the features of this texture, many factors are occurring, for instance diet and hydration, amount of collagen and hormones, and, of course skin care. A gradual decline in segmentation quality moreover occurs due to superimposing of high level details. As details increases thinner image patterns are developed and more easily damage the segmentation quality with the appearance of lines and irregular thin objects. The deterioration is also accompanied by a darkening of the background or boundary colour for an over absorption of the natural colouring pigment, melanin, by the top most cell layer og body organs. The texture also depends on its body location. In the case of image processing, we have considered the fact that texture appearance is changing with image recording parameters, that is camera, illumination and direction of view, a problem common to any real surface.

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