**MEDICAL IMAGE SEGMENTATION USING MULTIFRACTAL ANALYSIS**

**ABSTRACT**

We propose an algorithm utilizing multifractal analysis for automatic medical image segmentation. The objective of segmentation methods is to divide an image into segments based on elements with different characteristics such as tissues and bones. Many available methods focus on histogram or manual decomposition; however, in clinical situations these methods are often tedious and produce biased results. The proposed method provides an automatic segmentation algorithm, which eliminates problems associated with the traditional methods while simultaneously increasing the speed of the process. This algorithm is capable of reliably segmenting medical images by implementing multifractal analysis techniques. The resulting image can then be easily analyzed by medical professionals for diagnosing medical conditions. The outcome shows that the proposed method is more robust than the traditional method as well as more practical for real-time applications such as a virtual surgical environment.

**1. INTRODUCTION**

Image analysis has many applications in fields such as medical imaging, mining, robotics, and finance. Often, image analysis is employed in applications where there is too much data for human analysis or to detect features that the human eye struggles to detect. Image analysis deals with teaching a computer how to ''see''. In most cases, the aim is either to let the computer process data which are too numerous to be analyzed by human beings, or to be able to detect features in images that are not easily found by the human eye [18].

Magnetic resonance imaging, commonly referred to as MRI, is a non-invasive procedure for obtaining images of the body. Compared to X-ray computerized topography (CT), MRI images provide more detail without the use of potentially dangerous radioactive waves. An MRI provides high contrast, three-dimensional images which are invaluable for medical diagnosis and treatment [6, 7, 8]. MRI is based on Purcell [1] and Bloch's [2] work with nuclear magnetic resonance (NMR). All materials contain nuclei. The idea behind NMR is that materials containing nuclei composed of a non-even amount of neutrons, protons, or a mixture of the two have both a nuclear “spin” and a “magnetic moment”. Many materials (including biological tissue) have nuclei with the properties mentioned above, and as a result it is possible to image these materials by means of NMR methods [3]. The atoms of these materials, when exposed to radio frequency (RF) fields, emit radio signals. MRI takes advantage of this fact by using an RF field to stimulate these atoms, causing them to emit signals. These signals generate an electric current that is detected by a pickup coil that surrounds the patient or subject to be imaged. A computer processes the observed signal to create a sampled grayscale pattern, which constitutes an MRI image. Work done by Damadian [4] and Lauterbur [5] during the 1970’s has shown that NMR methods could have applications in medical diagnosis. Damadian found that the relaxation time (the period of time an atom continues to emit signals after ending exposure to an RF field) differs between different tissue types. The discovery of these variations in relaxation time is what allows tissues to be distinguished from surrounding tissues in an MRI image. Detectable relaxation times are divided into two types: T1 and T2. A signal received from a particular tissue is typically composed of both T1 and T2 values. This combination determines that signals characteristics. If an image is T1 based that means that tissues or elements of the generated image that have low T1 values will appear as bright spots in the image while those having high T1 values are shown to be darker. Conversely, T2 based images show high valued T2 tissues as being dark and low valued T2 tissues as bright. Traditional techniques cannot effectively process the volume of data that MRIs are capable of producing. Therefore, medical image analysis methods and techniques for visualization are of great value in the medical imaging field. There are three major topics of research in this area: cross-registration, intuitive visualization, and image segmentation. The goal of the latter most of these research topics is to efficiently identify important structural information concerning the subject’s pathology and anatomy. Image segmentation is often done manually and thus creates a bottleneck in clinical applications. This is standard, but is unacceptable in situations where it is crucial to identify many organs within the radiological data sets such as computer assisted neurosurgery. Other situations require the identification of tissue boundaries, especially those in which the relationship between therapeutic actions and morphological changes must be evaluated and understood. Obtaining statistically significant results demands that many data sets must be segmented. In applications like those mentioned above, traditional methods are suspect in part because of the amount of effort required, but also because it is difficult to reproduce results.

Over the last several years, multifractal analysis has been increasingly used in medical signal analysis [15, 17]. Multifractal analysis has been used to characterize a wide range of medical signals [16] including electrocardiogram signals, brain imaging, mammography, and bone imaging. This analysis is quite effective for image segmentation which characterizes a given region of the image. One example involves characterizing the pixels distribution heterogeneity of a region of the image. Multifractal models allow us to describe the scale-to-scale propagation of this distribution [19, 20]. There is much research on the use of this in mammography images [21, 22]. The applicability of the fractal geometry is accepted by the fact that, micro-calcifications usually appear as a cluster of bright spots with variant size and shape embedded in an inhomogeneous background of tissue. The inhomogeneous background also shows the self-similarity of fractal images in that a region containing the micro-calcifications clusters can be viewed [23, 24].

In this paper, we present a multifractal-based image segmentation algorithm that characterizes important parameters. The next section presents an overview of multifractal analysis followed by a derivation of the Hausdorff spectrum for signals and images. The third section provides the empirical framework for analysis and the underlying methodology. In the fourth section, results are discussed. Concluding remarks focus on implications of these methods for broader medical imaging applications and the area of future research.

**2. MATHEMATICAL BACKGROUND**

**2.1 MULTIFRACTAL ANALSYIS**

In this section, we describe the multifractal approach to image analysis. The essential difference between this approach and classical methods (canny edge detector, mathematical morphology etc.,) lies in the way they handle irregularity. Our study of multifractal analysis starts with the following definitions due to Vehel et al [6, 7, 8].

**Definition: -** Let  be a set. A paving on E is a set of subsets of  containing the empty set and stable under finite union and finite intersection. The pair  is called a paved space.

Let denotes  the power set of .

**Definition: -** Let  be a paved space. A Choquet -capacity on  is a function  with the following properties:

1.  is non-decreasing: if , then .
2. If  is an increasing sequence of subsets of , i.e , 
3. If is  a decreasing sequence of elements of , i.e., then 

Here we only consider Choquet capacities defined on , and taking values in with . Moreover, word capacity will stand for a Choquet -capacity on . Let  be a sequence of capacities defined on , and  a sequence of partitions of . We assume that the following conditions are met:

1. 
2. For all is an semi open interval.
3. For all  there exist  such that 
4. For all  where 

Let  which is defined when  and  when this limit exists. We call this quantity the pointwise  exponent of  at point  with respect to, although the usual definition involves the limit over all balls centered at, is given below:

Let  be a Borel measure defined on a compact set. For each point, define the *Local Singularity coefficients* as:

 (2.1)

where is an open-ball of diameter centered at the point and when the limit exists.  is often called the  coefficient. It reflects the local behavior of the measure  around. Points bearing the same coefficients can be grouped into sets, named Iso-Local Singularity sets, define as follows:



We can define above sets with  threshold value as follows



To characterize the above sets, now we will define set dimensions known as the *Hausdorff dimension*



where is a  of, , , .

Finally define 

The description  is called the *Local Singularity spectrum* sometimes it is also called  or Hausdorff spectrum of the multifractal measure.

1. Approaching multifractal analysis from a computational standpoint requires the use of discrete forms of the aforementioned measures and capacities [9, 11, 12]. Because the Hausdorff dimension is not computable, we use the computed box dimension in place of the Hausdorff dimension. Additionally, we replace the  by slope of the linear regression of the  of  against [10]. Then the abstract descriptions of multi-fractal analysis are useful for creating feasible computational tools for applications in images and signals. In equation (2.1), the points correspond with pixels that are from the actual image, open-balls are associated with blocks (windows) centered about each pixel, and measures are associated with functions of the intensities of gray levels.  is the sum of the pixel intensities inside of a region which is centered about pixel. Then represents the amount of gray at.  is defined by the equation:
2.  (2.2)
4. The above eqn. (2.2) represents an image’s intensity properties such as sharpness, spatial distribution, etc. We denote this as a sum measure of a given image.

**3. METHODOLOGY**

Below, we detail our multifractal image analysis technique. The difference that sets this approach apart from traditional methods is in how it handles irregularity.

1. Fig. 1 provides a flow chart for the steps of our method. We use our technique on several types of medical images. Segmentation by means of multifractal analysis is a viable solution for many different image categories.

Image

Compute the sum measure, , at each pixel

Compute the Box dimension Image

Thresholding

Segmented Image 1

Segmented Image 2

Segmented Image 3

**4. RESULTS**

**5. CONCLUSION**

Following the procedure described in the previous sections of this paper, we adopted a novel approach to automate the process of segmenting medical images. It is a very fast method, taking only a few seconds to segment MRI images. Beside this we also point out the simplicity of the approach. A foundation for the application of multifractal based MRI spatial analysis has been set forth. The exploratory medical image analysis inherent in multifractal analysis-based techniques and the resulting images provide a means of visually conveying tremendous amounts of information. This portrayal of the relationship between multifractal analysis and medical characteristics makes an important contribution to understanding medical images. The multifractal analysis-based segmentation method developed and demonstrated in this paper can be augmented further by integrating it with wavelet analysis.

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