A THEORETICAL STUDY ON PARTIALLY AUTOMATED METHOD FOR (PROSTATE) CANCER PINPOINT USING MAGNETIC RESONANCE IMAGING (MRI)

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Abstract

A Partially Automated method for (Prostate) Cancer pinpoint using Multi-parametric magnetic resonance imaging has been proposed in this paper, which can be used in guiding surgery. A Random Walker (RW) algorithm has been analyzed with seed initialization to perform (Prostate) cancer pinpoint using Magnetic Resonance Imaging (MRI). Segmentation can be done by using Random Walker (RW) algorithm which has to be considered to be a fastest method. Random Walker (RW) method can be used with multi-parametric magnetic resonance imaging (MRI) and then by using Support Vector Machine (SVM) method, we can determine the seed points in a partially automated manner. By using this method, more weights to the image can be assigned in order to produce improved segmentation process. The proposed method can also give high specificity rate without reducing the sensitivity which is better than earlier methods and fisher sign test can be also used to find the statistical differences.

Index terms:*Support Vector Machine, Random Walker, Magnetic Prediction, Magnetic Resonance.*

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1. INTRODUCTION

A (Prostate) cancer develops in a gland i.e. male reproductive system. It is one of the typical cancers which spreads in other parts of the human body especially bones and lymph nodes. Pain while urinating, sexual intercourse and erectile dysfunction are some of the symptoms of this cancer. Initial treatment is more important which the prostate specific antigen testing increases cancer detection, but does not decreases mortality [3], [10].

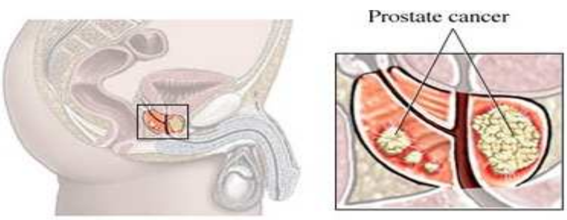

Fig-1: Prostate Cancer in human body

1.1 Prostate Imaging

The imaging methods used for (Prostate) cancer detection are Ultrasound (US) and Magnetic Resonance Imaging (MRI). The main drawback of Ultrasound (US) technique is poor tissue resolution, which cannot be used clinically. But compared to Ultrasound (US), MRI (Good Soft tissue Resolution) uses magnetic fields to locate and characterize (prostate) cancer [7], [19]. Multi-parametric prostate Magnetic Resonance Imaging (MRI) consists of 4 types which are follows:

1. Weighed Imaging (WI).
2. Diffusion Weighed Imaging (DWI).
3. Magnetic Resonance Spectroscopic Imaging (MRSI).
4. Dynamic Construct Enhanced Imaging (DCEI).

2. LITERATURE SURVEY

Accurate Automatic Analysis of Cardiac Cineimages

In this automated approach, they are 3 steps for analyzing the thickness and thickening of the images. First step is to segment then inner and outer wall tissue borders by using the geometric deformable model. In Second step, using Laplace equation, point-to-point correspondence between inner and outer borders of the tissue was found. In last step, Gauss Markov Random Field (GGMRF) model is used to reduce the errors. In this approach, the segmentation is based upon the ROC (Receiver Operating Characteristic) and DSC (Dice similarity Coefficients for higher accuracy [12] – [25].

3. EXISTING METHOD & DRAWBACKS

In earlier method, manual and fully (i.e. supervised and unsupervised) segmentation had been performed using multi-parametric MRI. By using semi-supervised cancer pinpoint, labeling of data requires laborious human annotation. According to Tiwari et al., representation of individual data is combined multi-kernel which is followed by semi-supervised dimensionally reduction, incorporated to a high dimensional data in a reduced space.

3.1 Drawbacks of Existing system

In previous method, Weighed and Apparent diffusion coefficient method is used instead of Random Walker (RW) and Support Vector Machine (SVM) method for prostate cancer localization [Artan et al.]. Manual seeds are initialized rather than all the multi-parametric images.

4. PROPOSED METHOD & ADVANTAGES

In the proposed method, Random Walker (RW) technique can be used for image segmentation which is used in multi-parametric images. This method combines multiple image segmentation [Wattaya et al.] results in which each can be obtained by using Random Walker (RW) algorithm after varying the number of user assigned seeds. Then it is compared with Locality preserving projections (LPP) method of [Grady et al.] and [Levin et.al] for edge weights by applying linear transformation to RGB color.

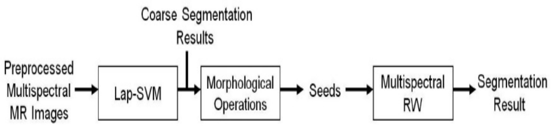

Fig- 2: Segmentation Process

4.1 Advantages of Proposed Method:

- To identify (Prostate) cancer pinpoint with multi-parametric MRI.
- Automated Seed initialization for RW algorithm.
- Several MR image types are combined optimally and automate the seed generation process for RW algorithm using discriminative learning techniques.

4.2 Algorithm

Step1: Laplacian-Support Vector Machine (Lap-SVM) is used to produce a rough estimate on tumor locations for a given a set of multi-parametric MR images.
Step2: Isolated pixels are removed from Lap-SVM (Laplacian-Support Vector Machine) output, and eccentricity values are determined for each of the connected components in the resulting binary image
Step 3: Applying erosion operation on the binary image.
Step4: Assigning a positive seed at the center of the remaining connected component(s) and a negative seed to the location corresponding to the minimum Lap-SVM (Laplacian-Support Vector Machine) value in the unthresholded Lap-SVM (Laplacian-Support Vector Machine) output.

5. ARCHITECTURE

In previous work, segmentation method is designed by combining conditional random fields (CRF) with a cost-sensitive SVM, which allowed incorporating spatial information in the segmentation process. Incorporation of spatial information is achieved through seed points that are selected via SVM (Support Vector Machine) in the proposed method. These seed points allow us to accurately localize desired regions, higher specificity and sensitivity rates compared to (seeded) spatial algorithm in our segmentation scheme.

List of Modules:
1. *Normalization*
2. *Anisotropic Filtering*
3. *Multi-parametric RW*
4. *Seed Generation using Laplacian SVM*

5.1 Normalization

Multi-parametric MRI dataset can be used, which can consist of three different types of MR images. Each multi-parametric component represents a particular anatomical and functional response of the prostate gland. Feature vectors used in our segmentation framework are the intensity values of the multi-parametric MR images. The prostate consists of various zones such as CG (Central Gland) and PZ (Peripheral Zone). PZ (Peripheral Zone) region is located at the back of the prostate gland, which is close to the rectum [23- 27].

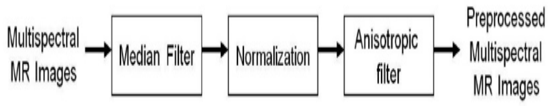

Fig-3: Normalization process

For each of the multi-parametric images, PZ (Peripheral Zone) region intensities were normalized such that intensities in the PZ (Peripheral Zone) region had zero mean and unit standard deviation for all the training and testing subjects for a particular multi-parametric image type. This process brings intensities of different types of MR (Magnetic Resonance) images within the same dynamic range, improving the segmentation methods [5], [10], [11].

5.2 Anisotropic Filtering

Magnetic resonance images are typically corrupted by thermal noise due to receiver coils. Therefore, many earlier studies proposed various filtering schemes to remove noise before doing any further processing on them [30]. However, while suppressing the noise, we want to simultaneously preserve the information-bearing structures such as edge boundaries. Anisotropic filtering allows us to smooth PZ (Peripheral Zone) regions of multi-parametric images without blurring the tumor nodule edges. The diffusion equation for an image u is given by,

$$\frac{\partial u}{\partial t} = \mathrm{div}(\rho(|\nabla u|) \cdot |\nabla u|) \quad (1)$$

Equation encourages smoothing within PZ (Peripheral Zone) region while preserving tumor boundaries. This method will not cause interregional blurring as often caused by traditional smoothing techniques. Note that anisotropic filtering needs to be applied on the median-filtered and normalized images for a successful application as noted in our earlier study [25-29].

5.3 Multi-Parametric RW

RW (Random Walker) algorithm is a seeded segmentation technique that formulates the classical segmentation problem in terms of a discrete combinatorial problem. An edge connecting two vertices is denoted as ***eij***. A weighted graph has a value assigned to each edge called a weight denoted by ***wij*** . In the original RW formulation and used the typical Gaussian weighting function given by,

$$w_{ij} = \exp(-\beta \, (g_i - g_j)^2) \quad \textbf{(2)}$$

Where, ***gi*** indicates the image intensity at pixel ***i,*** and the value of the scalar is selected based on experience. Linear weighted combination of features yields a final image that yields improved RW (Random Walker) segmentation for the given set of seeds. Edge weights for the multi-parametric problem ***wij*** can now be written as,

$$w_{ij} = \exp\left\{ -\beta \left(\sum_{n=1}^{N} k_n (g_{ni} - g_{nj}) \right)^2 \right\}. \quad \textbf{(3)}$$

5.4 Seed Generation Using Laplacian SVM

In this algorithm, the Seeds are manually initialized. Therefore, we have compared various methods, namely, support vector machines (SVM), transductive support vector machines (TSVM) and Laplacian support vector machines (Lap-SVM), to develop a seed selection technique most suited for (prostate) cancer pinpoint. SVM (Support Vector Machine) method is used only for seed generation for the RW algorithm, not the actual segmentation [15]. The geometry of data is modeled as a graph in which nodes represents the labeled and unlabeled samples connected by weights ***wij*** resulting,

$$||f||_M^2 = \frac{1}{(\ell + u)^2} \sum_{i,j=1}^{\ell+u} w_{ij} (f(\mathbf{x}_i) - f(\mathbf{x}_j))^2 \quad \textbf{(4)}$$

6. CONCLUSIONS

We presented a framework for automatically localizing prostate cancer with multi-parametric MR images using a new approach of partially supervised segmentation in this paper. Proposed Random Walker [RW] method produce improved segmentation results by assigning more weights to the images. Our study show that significantly improved segmentation results could be obtained with the proposed method compared to earlier developed methods. Fisher's sign test can be also used to show improvements with our method are statistically significant. Multiple initializations for the optimum values increases the computation cost slightly, and decreasing this computation is a subject of our future study.

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