Normalization of T2W-MRI Prostate Images using Rician a priori

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ABSTRACT

Prostate cancer is reported to be the second most frequently diagnosed cancer of men in the world. In practise, diagnosis can be affected by multiple factors which reduces the chance to detect the potential lesions. In the last decades, new imaging techniques mainly based on MRI are developed in conjunction with Computer-Aided Diagnosis (CAD) systems to help radiologists for such diagnosis. CAD systems are usually designed as a sequential process consisting of four stages: pre-processing, segmentation, registration and classification. As a pre-processing, image normalization remains an important process to later design robust classifier and overcome the intensity variations inter-patients. As a pre-processing, image normalization is a critical and important step of the chain in order to design a robust classifier and overcome the inter-patients intensity variations. However, little attention has been dedicated to the normalization of T2W-MRI prostate images. In this paper, we propose a method based on a Rician *a priori* in order to normalize T2W-MRI prostate images. A comparison with the state-of-the-art methods is also provided. The normalization of the data is assessed by comparing the alignment of the patient Probability Density Function (PDF)s in both qualitative and quantitative manners. In both evaluation, the normalization using Rician *a priori* outperforms the other state-of-the-art methods.

Keywords: Prostate cancer, T2W MRI, Normalisation, pre-processing, computer-aided diagnosis

1. DESCRIPTION

The prostate gland is part of men reproductive system and have an inverted pyramidal shape. Figure **??** shows a zonal classification of this organ.[1] Based on this classification the gland is divided into three distinct regions:(i)Central Zone (CZ), (ii)Transitional Zone (TZ), and (iii)Peripheral Zone (PZ) where each represent, 20-25%, 5% and 70% of the prostate respectively. In Magnetic Resonance Imaging (MRI) images, the tissue of PZ and TZ are usually merged together as part of the central gland and are difficult to distinguish. Prostate Cancer (CaP) has been reported the second most frequently diagnosed cancer of men accounting for 13.6% .[2] In United States, aside from skin cancer, CaP was considered to be the most commonly diagnosed cancer among men, implying that approximately one in 6 men will be diagnosed with CaP during their lifetime. *American cancer society* also reported an estimated 233,000 new cases of prostate cancer in 2014.[3] CaP is most likely to appear in PZ rather than TZ and CZ, respectively. The CaP diagnosis is usually performed through Prostate-Specific Antigen (PSA) control test and Transrectal Ultrasound (TRUS) biopsy. In PSA test, the higher than normal level of PSA can indicate abnormalities in the prostate. However other factors, such as prostate infection, irritations can lead to a higher level of PSA. After this test, the candidate with higher risk factor are considered for TRUS, where atleast six different samples are taken randomly from the right and left part of the three different zones. Due to the lack of reliability of PSA test, further investigations using MRI-Computer-Aided Diagnosis (CAD) are motivated. maybe one more sentences to advertise MRI In the past decades, several CAD systems have been proposed in order to assist the radiologists with their diagnosis. These systems are usually designed as a sequential process consisting of four stages: pre-processing, segmentation, registration and classification. As a

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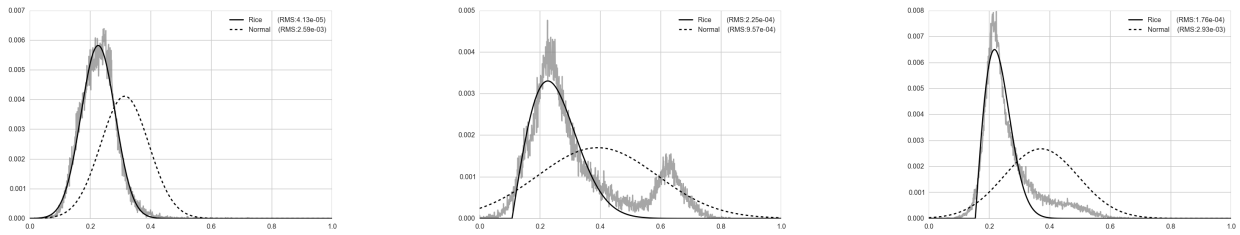

(a) (b) (c)

Figure 1: Visual evaluation of the goodness of fitting using Rician and Gaussian distribution.

pre-processing steps, image normalization is an important step of the chain. This step is highly crucial in order to achieve a robust classification of segmentation and overcome the inter-patients intensity variations. Patient variability is a common and occurrence fact, even using the same scanner, protocol or sequence parameter, hence the main aim of the normalization of the MRI data is to remove the variability between patients and enforce the repeatability of the MRI examinations. Few approaches have been proposed in the past to address this issue. Artan *et.al.*[4,5] and Ozer *et.al.* proposed to normalize the T2-W images by computing the standard score (i.e. *z-score*) of the pixels of the PZ as:

$$I_s(x) = \frac{I_r(x) - \mu_{pz}}{\sigma_{pz}}, \forall x \in PZ \tag{1}$$

Where, $I_s(x)$ and $I_r(x)$ are the standardized and the raw signal intensity, respectively and μ_{PZ} and σ_{PZ} are the mean and standard deviation of the PZ signal intensity. This transformation enforces the image Probability Density Function (PDF) to have the zero mean and a unit standard deviation. Lv *et.al.*[6] proposed to transform and match the PDF of T2-W image using some statistical landmarks such as median and different quantiles. His method is based on the assumption that MRI images from the same sequence should share the same PDF appearance. Viswanath *et.al.*[7] proposed a variant of the previous method for normalization of the T2-W MRI images. In their proposed method instead of computing the PDF of an entire image, the PDF of the largest region in the foreground are computed and aligned in the same manner as.[6]

In this paper, we propose a method based on a Rician *a priori* in order to normalize T2W-MRI prostate images. abit more information maybe

2. METHODOLOGY

3. RESULTS

3.1 Qualitative

3.2 Quantitative

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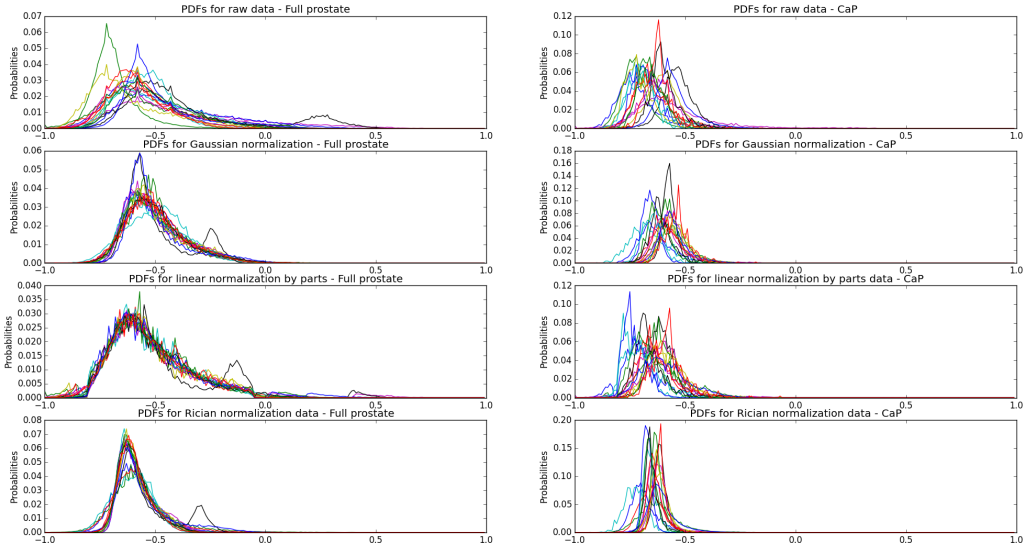
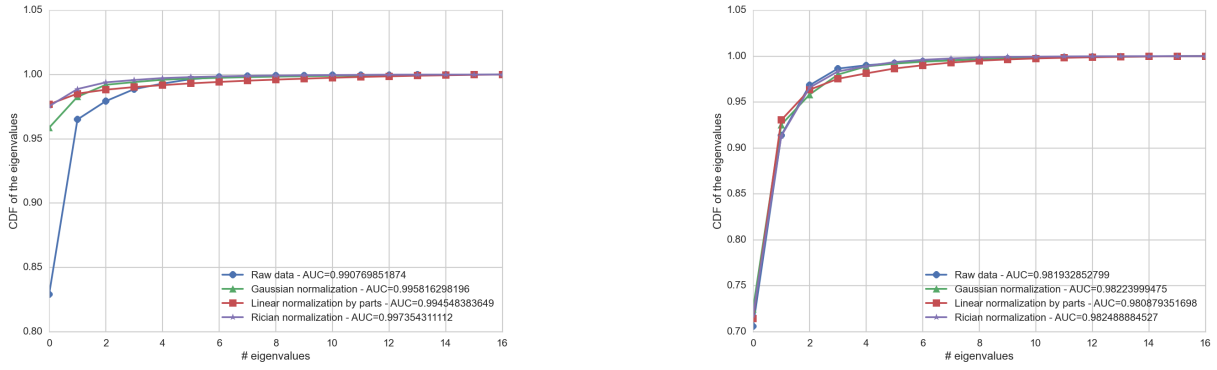


Figure 2: Qualitative evaluation by visual inspection of the alignment of the PDFs for the full prostate and the CaP.



(a) (b)

Figure 3: Spectral evaluation using PCA decomposition: (a) evaluation considering the full prostate, (b) evaluation considering only the CaP.

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