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 is a critical and important step of the chain in order to design a robust classifier and overcome the inter-patient 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

Prostate Cancer (CaP) has been reported the second most frequently diagnosed cancer of men accounting for 13.6%.[1] In United States, aside from skin cancer, CaP was considered to be the most commonly diagnosed cancer among men, implying that approximately 1 in 6 men will be diagnosed with CaP during their lifetime. The *American cancer society* also reported an estimated 233,000 new cases of prostate cancer in 2014.[2] To address these dramatic issues, more systematic screenings are organized through Prostate-Specific Antigen (PSA) test with further Transrectal Ultrasound biopsy if necessary. However, these tests are unreliable or invasive and that is why further investigations using Magnetic Resonance Imaging (MRI)-Computer-Aided Diagnosis (CAD) are motivated. 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 pre-processing steps, image normalization is an important step of the chain. Normalization is a highly crucial step to overcome the inter-patient intensity variations occurring, enforce the repeatability, and achieve a robust classification.[3] However, little attention has been dedicated to the problem of normalization of T2W-MRI prostate images.[3] Artan *et al.*[4,5] and Ozer *et al.*[6,7] proposed to normalize the T2W-MRI images by computing the standard score (i.e., *z-score*) of the Peripheral Zone (PZ) pixels such as:

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

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

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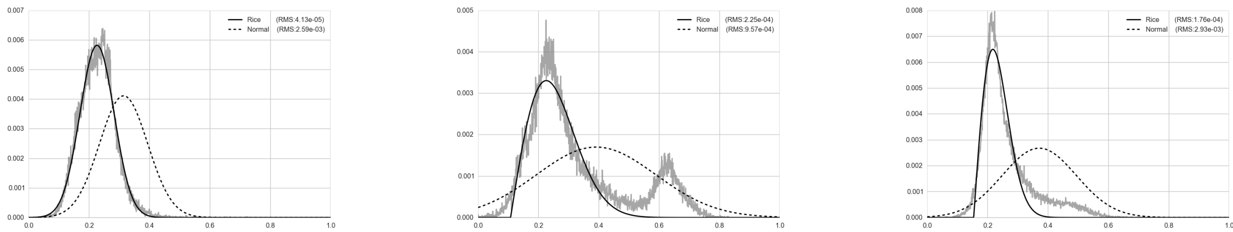


(a) (b) (c)

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

Density Function (PDF) to have a zero mean and a unit standard deviation. Lv *et al.*[8] used the method proposed by Nyul *et al.*[9] For a given patient, some specific landmarks (i.e., median and different percentiles) of the current PDF match the same landmarks learned during a training phase from several patients. Viswanath *et al.*[10] used a variant of the previous method by segmenting first the image and keeping only the largest region to build the PDF. In this paper, we propose a method based on a Rician *a priori* in order to normalize T2W-MRI prostate images. We emphasize the use of a Rician distribution before to present the methodology allowing to normalize the images. Both qualitative and quantitative results are given and compared with the previous stated methods.

2. METHODOLOGY

As stated in Sect. 1 proper normalization of the MRI data during pre-processing is a key problem that has been addressed from a parametric and non-parametric point of view. We believe that normalizing MRI data using a parametric model based on Rice distribution would improve the results for the parametric case. Expecting this improvement by changing the data model from Gaussian to Rice distribution is reasonable since Bernstein *et al.*[?] statet that MRI data follows a Rayleigh distribution for low Signal-to-Noise Ratio (SNR) scenarios while it appears closer to a Gaussian distribution when SNR increases.

3. EXPERIMENTS

The experiments are conducted on a subset of public multi-parametric MRI prostate dataset available at `http://visor.udg.edu/i2cvb/`.[11] This dataset was acquired from a cohort of patients with higher-than-normal level of PSA. The acquisition was performed using a 3T whole body MRI scanner (Siemens Magnetom Trio TIM, Erlangen, Germany) using sequences to obtain T2W-MRI. Aside of the MRI examinations, these patients also underwent a guided-biopsy. Finally, the dataset was composed of a total of 20 patients of which 18 patients had biopsy proven CaP and 2 patients were "healthy" with negative biopsies. In this study, our subset consists of 17 patients with CaP. The prostate organ as well as the prostate zones (i.e., PZ, Central Gland) and CaP were manually segmented by an experienced radiologist.

4. RESULTS

4.1 Qualitative

Figure 2 depicts the alignment of the different PDFs using the different methods implemented. All the methods seem to address the problem of the PDF alignment of the full prostate data. However, the Rician normalization seems to outperform the other methods when focusing solely on the CaP data. The PDF computed in this specific area is more skewed from its original shape in the case of the linear normalization by parts than with the two other normalization strategies.

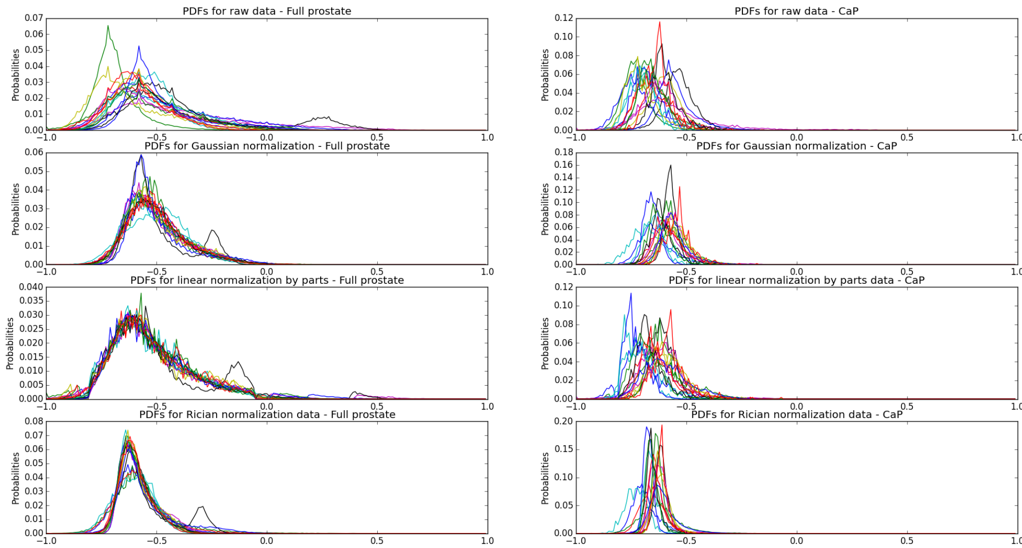
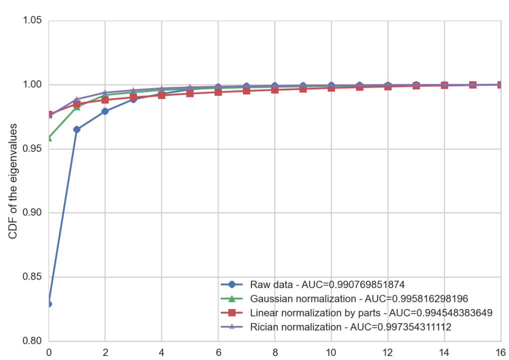
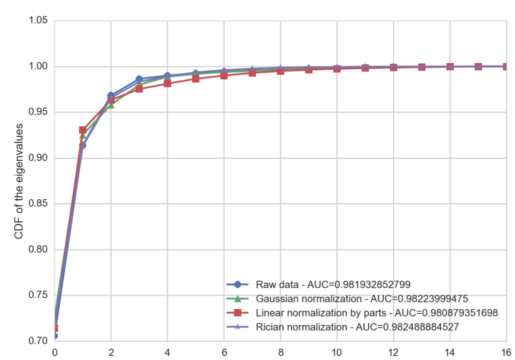


Figure 2: Qualitative evaluation by visual inspection of the alignment of the PDFs for the full prostate and the CaP.



(a)



(b)

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

4.2 Quantitative

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