

Normalization of T2W-MRI Prostate Images using Rician a priori

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Introduction

- ► Prostate Cancer (CaP) has been reported the **second** most frequently diagnosed cancer of men accounting for 13.6% [F⁺10].
- Computer-Aided Diagnosis systems have been proposed in order to assist the radiologists and generally consist of four stages: (i) **pre-processing**, (ii) *segmentation*, (iii) *registration*, and (iv) *classification* [L⁺15].
- Normalization is crucial to overcome the *inter-patient* intensity variations, enforce the *repeatability*, and achieve a *robust* classification.

State-of-the-art method

- Artan et al. [A+10] and Ozer et al. [O+10] used the **z**-score (see Eq. (1)) to normalize T2W-MRI.
- Lv et al. [L+09] and Viswanath et al. [V+12] used methods based on piecewise-linear normalization [Nea00].

Contributions

We proposed two alternative methods:

- (i) a model-based approach using Rician a priori;
- (ii) a non-parametric based approach based on the Square-Root Slope Function (SRSF) representation [SKJJ11].

Model-based normalization

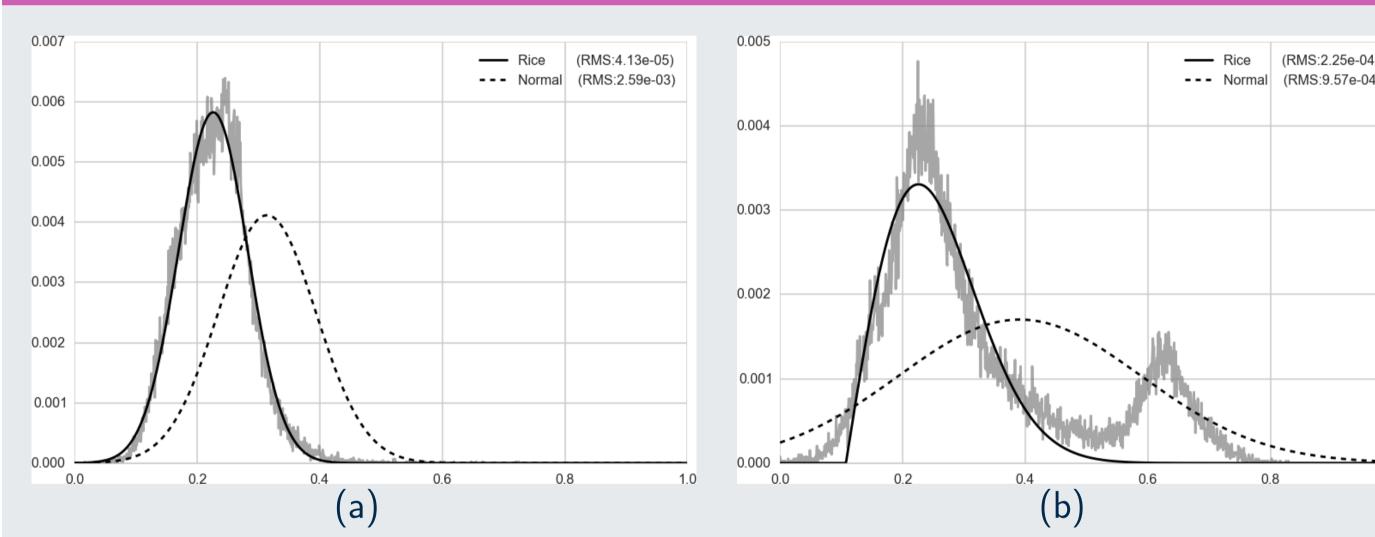


Figure 1: Visual evaluation of the goodness of fitting using Rician and Gaussian distribution.

Gaussian normalization

Rician normalization

$$I_{s}(x) = \frac{I_{r}(x) - \mu_{R}}{\sigma_{R}}, \qquad (2)$$

 $I_r(x) - \mu_G$ wher

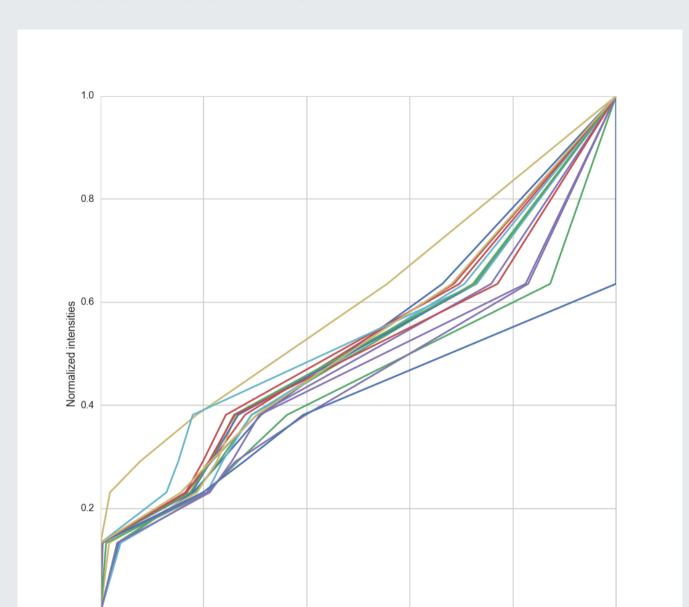
$$\mu_{\mathsf{R}} = \sigma \sqrt{\frac{\pi}{2}} \; \mathsf{L}_{1/2} (-\frac{\nu^2}{2\sigma^2}) \; , \qquad \qquad (3)$$

$$\sigma_{\rm R} = 2\sigma^2 + \nu^2 - \frac{\pi\sigma^2}{2} \mathsf{L}_{1/2}^2 \left(\frac{-\nu^2}{2\sigma^2} \right) \; . \tag{4}$$

- ► MRI data theoretically follows a Rayleigh distribution for a low SNR scenarios while it appears closer to a Gaussian distribution when the SNR increases [Bea89].
- ► The Rician model better fits the data than the Gaussian model in terms of RMS.

Non-parametric normalization

Piecewise-linear normalization



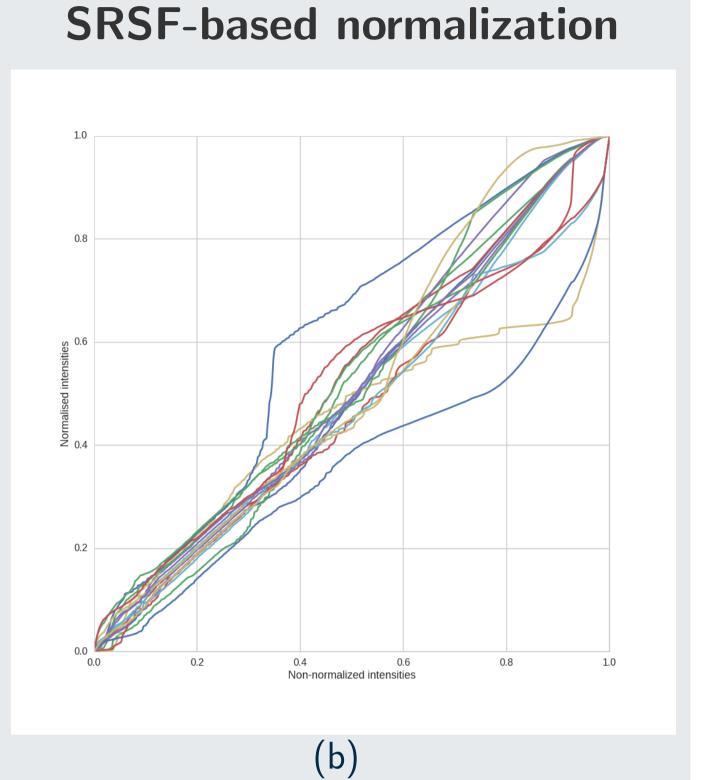


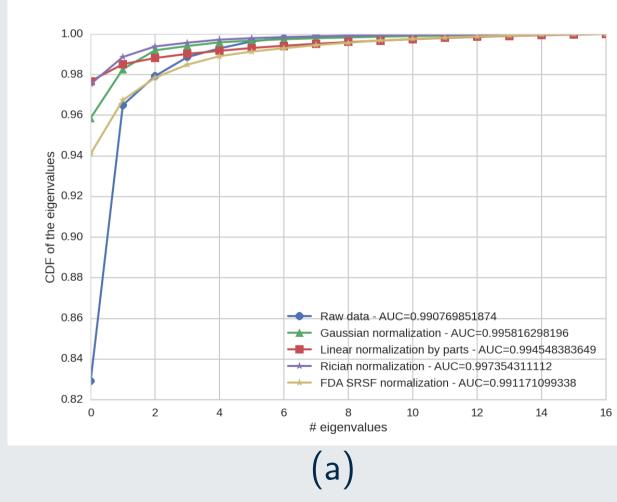
Figure 2 : Comparison of warping function obtained with (a) piecewise-linear normalization and (b) SRSF-based normalization.

- Minimize the distance between a set of standardized landmarks $\mu_{\mathbf{i}}$ (i.e., atlas) and a set of nonnormalized landmarks $\lambda_{\mathbf{i}}$.
- Minimize the distance between a mean PDF μ_f (i.e., the Karcher mean) and a given patient PDF f_i .
- SRSF-based normalization lead to smoother transition than piecewiselinear normalization.

T2W-MRI prostate dataset

- ➤ 3 Tesla whole body MRI scanner.
- ▶ 17 patients manually segmented by experienced radiologist.
- ► Publicly available at http://visor.udg.edu/i2cvb/.

Quantitative results



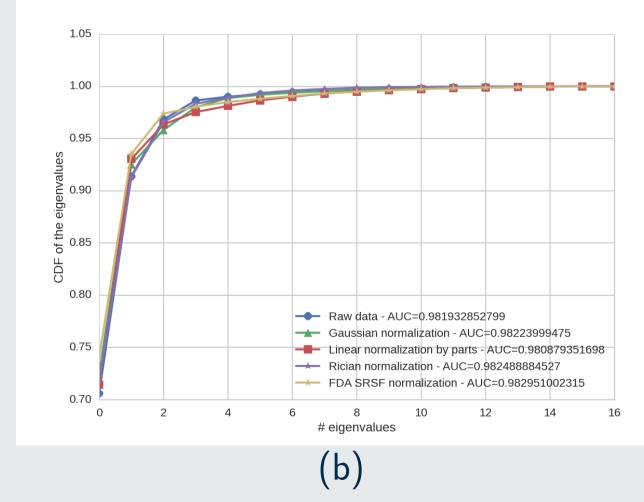


Figure 3: Eigenvalue decomposition to evaluate the alignment of the PDFs: (a) evaluation considering the full prostate, (b) evaluation considering only the CaP.

➤ Rician normalization outperforms the other methods: Area Under this Curve of **0.9974** and **0.9824** considering the full prostate and CaP, respectively.

Qualitative results

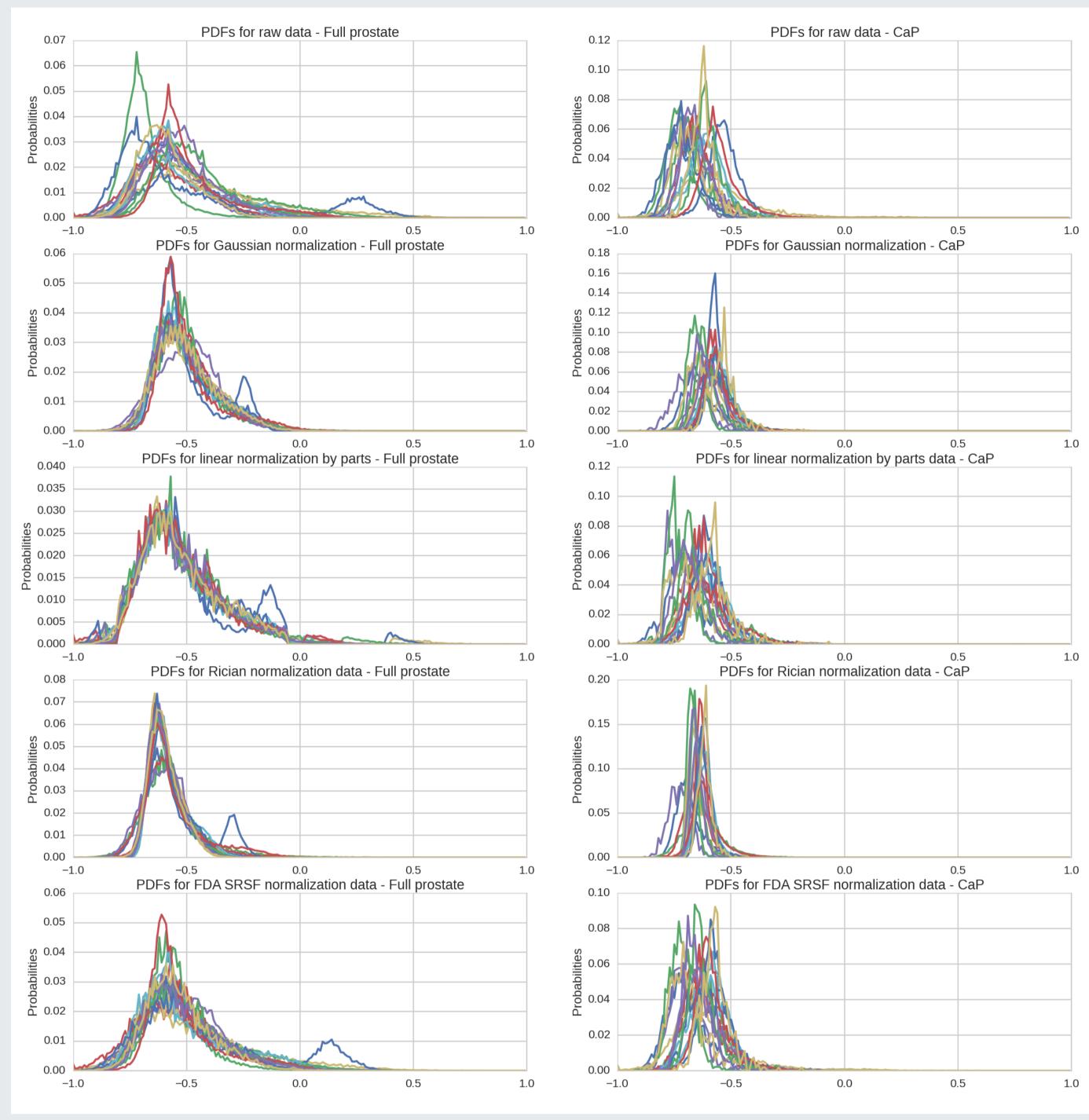


Figure 4: Qualitative evaluation by visual inspection of the alignment of the PDFs for the full prostate and the CaP.

- ► All the methods address the problem of the PDF alignment of the full prostate data.
- ► However, the Rician normalization outperforms the other methods when focusing solely on the CaP data.

Conclusion

Comparisons show that the Rician normalization outperforms the Gaussian, SRSF-based, and piecewise-linear normalization for T2W-MRI prostate images normalization.

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