Accuracy Enhancement of Automatic Prostate Tumor Detection using Additional Deformable Registration based Atlas Information: Automated Classifier using Permeability Parameters.

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INTRODUCTION: The prostate is anatomically composed of central, peripheral, and transitional zones developed by McNeal [1–2]. In the peripheral zone, 70% of prostate cancers arise. In addition, 20% of prostate cancers arise in the transitional zone (Figure 1). In this study, we sought to evaluate accuracy enhancement for prostate tumor detection of support vector machine classifier using deformable registration based atlas information as well as permeability parameters.

MATERIALS AND METHODS: In thirty seven patients with radical prostatectomy, MR images were obtained, including T2WI and dynamic contrast enhanced MR imaging for Brix perfusion analysis (3T; Gradient echo; temporal resolution, 3 sec; 200 dynamics) [3]. Figure 2 shows overall procedure. Each prostate was manually segmented into transitional zone and other zone (central and peripheral) by an expert radiologist and registered by FSL FNIRT deformable registration method [4] into an optimized template (Figure 3). Every Automated classifier was generated by support vector machine (SVM) which comprehensively evaluated 12 permeability parameters (Kep, Kel, AH, time of arrival (TA), time to peak, peak signal, upslope at TA, upslope to peak, downslope, area under curve (AUC), RMSE and) and atlas information (transitional or other zone) which was estimated by deformable registration. Three or four ROIs were picked at largest cancer and normal (Cancer N=41, Normal N=71) on transitional zone and peripheral zone per each patient, if possible. Pathology map was regarded as the reference standard. The sensitivity, specificity, accuracy and AUC of ROC were compared with and without atlas information. Classification was validated by 10-folding cross validation with 20 repetitions.

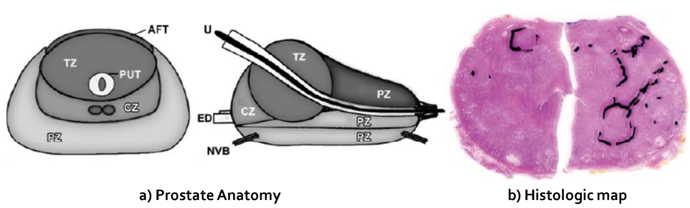

Figure 1 Schematics show the anatomy of the prostate in transverse and sagittal planes (a), and histologic map after prostatectomy (b)

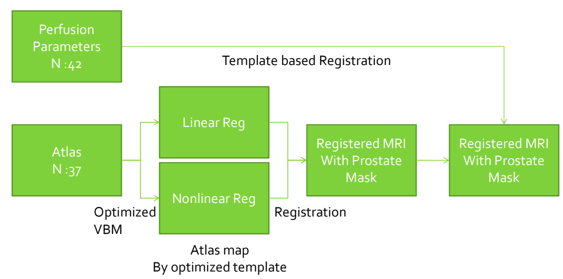

Figure 2 Overall procedures for CAD with atlas template based registration

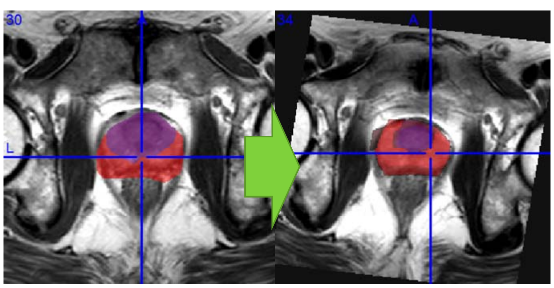

Figure 3 Deformable Registration with Prostate Segmented Mask (red, prostate; purple, transitional zone)

Table 1 Selected features by forward feature selection

	-Atlas	+Atlas
Features	Kep / Kel / AH / TA / TPeak / SPeak / Taslope / UpSlope_CurveTA / UpSlope_SPeakbyTtoP / UpSlope_SPeakbyTtoP50 / DownSlope / AUC / RMSE /	Kep / Kel / AH / TA / TPeak / SPeak / Taslope / UpSlope_CurveTA / UpSlope_SPeakbyTtoP /Initial UpSlope_SPeakbyTtoP50 / DownSlope / AUC / RMSE / Atlas
Selected Features	Kep, Kel, Taslope , UpSlope_SPeakbyTtoP , UpSlope_SPeakbyTtoP50	Kep, Atlas, Tpeak, SPeak , AUC

RESULTS: After forward feature selection (Table 1), atlas information was survived. Sensitivity, specificity, accuracy, and AUC of ROC were greater in automated classifier with atlas information (86.5±0.02%, 95.5±0.01%, 92.2±1.08%, 92.9±0.00 respectively) than in that without atlas information (82.6±0.02% , 90.3±0.01%, 87.5±1.10%, and 87.8±0.00%, respectively) (paired t-test, all p < .000) in Table 2.

Table 2 CAD Accuracy

	Permeability	Permeability + Atlas infor.*
Sensitivity	82.6±0.02%	86.5±0.02%
Specificity	90.3±0.01%	95.5±0.01%
Accuracy	87.5±1.10%	92.2±1.08%
AUC of ROC	87.8±0.00	92.9±0.00

* paired *t* test ($p < 0.000$)

DISCUSSION AND CONCLUSION: Atlas information significantly increases accuracy of the automated classifier for prostate cancer detection. Therefore, automated classifier, which indicates the presence of prostate cancer by comprehensively analyzing various permeability parameters with atlas information, can improve the diagnostic accuracy of MR in prostate cancer detection.

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