Effective 3D Object Detection and Regression Using Probabilistic Segmentation Features in CT Images

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1. Supplementary Material

The success of an end-to-end computer aided diagnosis system, from images to decisions, critically depends on two factors: 1, whether the image features can exploit different, diverse or heterogeneous statistical properties of the observed object (e.g., lesion, polyp, nodule, etc.), in a information-theoretical sense; 2, whether the classifier, regressor or other models can capture the incremental information gain by accumulating or fusing a set of diverse features, and convert it as effective discriminative power.

In this paper, we provide answers for the two questions above, using colonic polyp detection in CT images as a study case, without loss of generality. 1, The proposed probabilistic segmentation (PSM) features demonstrate excellent discriminative ability on classfying positives from negatives, and substantial information diversities in class-specific data distributions. Through all initiated by the supervised segmentation process, PSM features capture a diverse range of channels of information or cues, in the joint spatial space of segmentation probability output and original image (Section 2). The probability density function plots of a subset of PSM features, over both positive and negative candidate populations are shown in Fig. 1. The exampled six PSM features show quite different positive-negative distribution plots, which is the essence for better performance (or more information gain) when fused together. 2, The presented Bayesian soft-gating tree classifier (Section 4), using multiple instance relevance vector machine [1] as element node-classifier, and probabilistic multiple instance regression algorithm (Section 3) are capable of effectively and robustly fusing a set of dozens or even hundreds of heterogeneous features to build a statistically stronger model for optimized performance. Both classifier and regressor have intrinsic probabilistic formulations which naturally facilitates generality on testing data. These two factors contribute to our best state-of-the-art performance, in a large multi-site clinical dataset of 770 CT volumes (from US, Europe and Asia).

References

[1] V. Raykar, B. Krishnapuram, J. Bi, M. Dundar, and R. Rao. Bayesian multiple instance learning: automatic feature selection and inductive transfer. In *ICML*, pages 808–815, 2008. 1
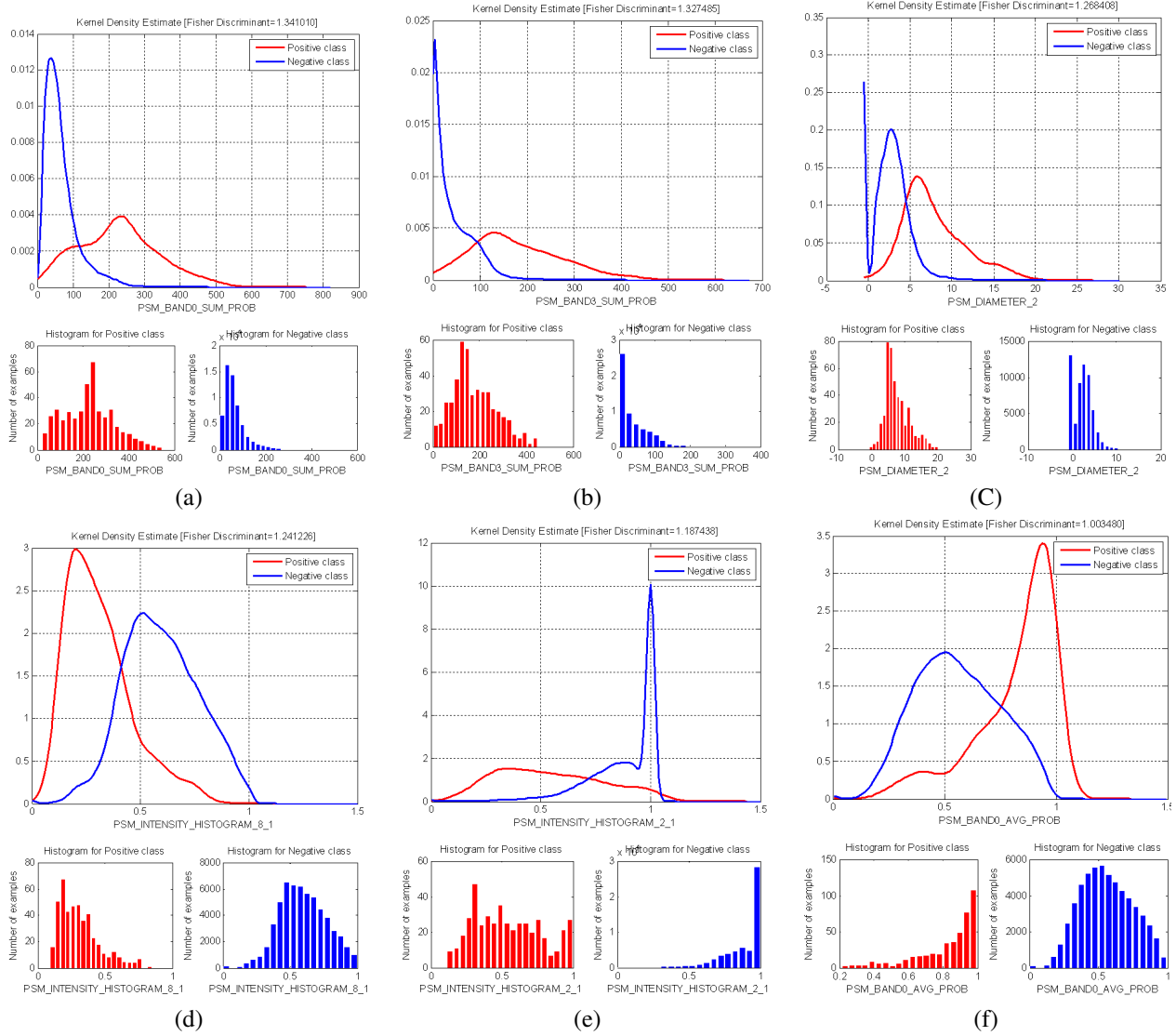
Figure 1. The probability (kernel) density function plots of a subset of PSM features, over both positive (red) and negative (blue) candidate populations. Through (a,b,c,d,e,f), their distributional diversities are evident, which is a prerequisite for statistical information gain when used as a group. (a,b) are $ProbSum_k; k = 0, 3$ features; (c) is D_2; (d,e) are two multiscale intensity histogram features, and (e) is $ProbAvg_0$ feature.