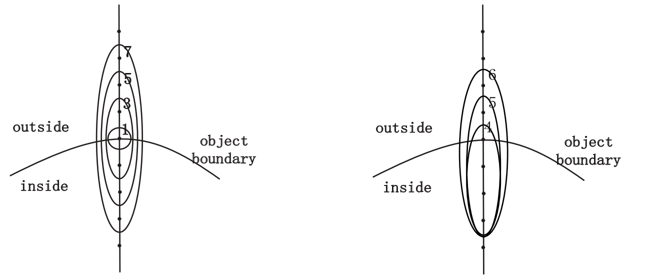
# Medical Image Segmentation Using Descriptive Image Features

Meijuan Yang
meijuan.yang@opt.ac.cn
Yuan Yuan
yuany@opt.ac.cn
Xuelong Li
xuelong_li@opt.ac.cn
Pingkun Yan
pingkun.yan@opt.ac.cn

Center for OPTical IMagery Analysis and Learning (OPTIMAL),
State Key Laboratory of Transient Optics and Photonics,
Xi'an Institute of Optics and Precision Mechanics,
Chinese Academy of Sciences,
Xi'an, Shaanxi P. R. China, 710119




(a) (b)

Figure 1: Two patterns of NVFPs are given: (a) appearances of points have low similarity both inside and outside the object, and (b) the appearance of the pixels inside the object is similar. Each ellipse stands for one case in our new profile. The points within the ellipse represent the locations of the sample points and the number marked on the ellipse represents the number of the sample points.

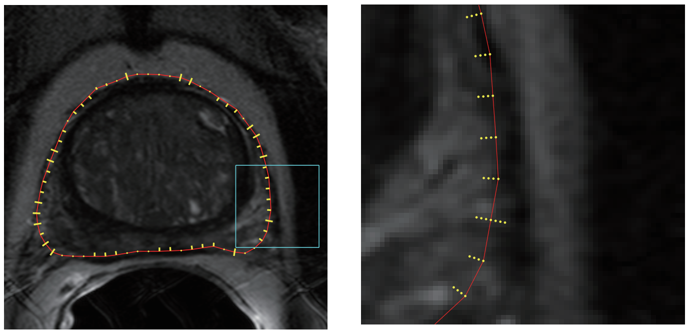
**Introduction.** Segmentation of medical images is an important component for diagnosis and treatment of diseases using medical imaging technologies. However, automated accurate medical image segmentation is still a challenge due to the difficulties in finding a robust feature descriptor to describe the object boundaries in medical images. In this paper, a new normal vector feature profile (NVFP) is proposed to describe the local image information of a contour point by concatenating a series of local region descriptors along the normal direction at that point. To avoid trapping by false boundaries caused by non-boundary image features, a modified scale invariant feature transform (SIFT) descriptor is developed. The number and locations of sample points for building NVFP are determined for each contour point, which are constrained by the neighboring anatomical structures and the statistical consistency of the training features. Finally, NVFP is incorporated into a model based method for prostate MR image segmentation.

**The Modified SIFT Feature.** First, a difference-of-Gaussian pyramid is computed to get the gradient magnitude and orientation for each point of the image. Second, the key point of SIFT is located. In our work, we aim to segment the anatomical structures in medical images. Thus, the contour points of the structures of interest are selected to be the key points. Third, the main orientation of SIFT is modified. In order to avoid ambiguities and improve the coherence in different images, we propose to use the normal directions of the contour at the key points for the main orientations, which achieves invariance to image rotation. Lastly, the key point descriptor as in the original SIFT is extracted.

**Normal Vector Feature Profile.** In deformable models, the point distribution model (PDM) is employed to represent the contour and the feature of NVFP is used to describe the contour point. The next three steps illustrate how NVFP is obtained.

- For each contour point, sample $k$ points using a fixed spacing evenly from both sides along the normal direction.
- Stack the modified SIFT feature of the sample points and form the feature vector of NVFP.
- Eliminate dissimilar features of the inhomogeous surroundings from NVFP.

According to the constraints of the surrounding anatomic structures, we design two patterns of NVFPs. In each pattern, there are several cases for the contour points, as shown in Fig. 1. First, appearances of some points have low similarity both inside and outside the object in different images. For this pattern, points of equal number are sampled for the interior and exterior when NVFP is trained. In most cases, the pixels outside of the object boundary can have quite different appearances. Therefore, the second pattern is to eliminate the inconsistent features caused by the different exterior structures.



(a) (b)

Figure 2: The number and locations of the sample points for the contour points are optimized when the NVFPs are built.

Each NVFP is specified by the number and locations of sample points, which is described in detail in Fig. 1. Then, we compute the consistency for each NVFP

$$C = \frac{L}{\sum_{l=1}^{L} \sigma(l)}, \tag{1}$$

where $L \leq k$ and $\sigma(l)$ is the standard deviation of the feature of $l$th sample point in the profile. As illustrated in Fig. 2, the number and locations of sample points for each contour point are shown.

**Image Segmentation Model.** A new energy function is defined.

$$E = E_{shape} + E_{NVFP}, \tag{2}$$

where $E_{shape}$ represents the energy of constrained shape from training images. $E_{NVFP}$ denotes the variation of NVFP appearance. $E_{shape}$ is determined by the shape model which derives from the principal component analysis (PCA) of training shapes. The training of local appearance model is described in preceding section. Minimizing $E_{NVFP}$ is to compute the the NVFPs in test image and match it with the training NVFPs, and then guide the contour deformation.

**Experiments.** In our experiments, 40 MR images of the prostate were used to validate the performance of the proposed method. Some qualitative results of the segmentation are given in Fig. 3 showing that ASM with NVFP is more likely to latch on the weak and ambiguous boundaries, and quantitative results in Table 1 showing that feature of NVFP improves the segmentation performance greatly.

Table 1: Mean Absolute Distance between the automatic segmentation results and the manual segmentation results(unit in mm)

| Algorithm | Mean± std | Min | Max | Med |
|---|---|---|---|---|
| ASM with NVFP | 1.30±0.41 | 0.87 | 2.30 | 1.23 |
| Classic ASM | 1.74±0.45 | 1.01 | 3.30 | 1.72 |

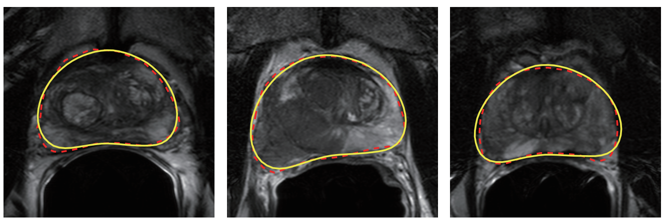


Figure 3: Some qualitative segmentation results of ASM based methods. The ASM based segmentation results are shown as yellow solid line and the manual segmentations are shown as red dash line.