Chapter 5

Using the GGM-SSM as a Prior for Segmentation

Segmentation algorithms play a major role in medical image analysis. However, due to typical medical image characteristics as poor contrasts, grey value inhomogeneities, contour gaps, and noise the automatic segmentation of many anatomical structures remains a challenge. Low-level algorithms as region growing, thresholding or simple edge-detection are often bound to fail or require heavy user interaction to lead to acceptable segmentation results in 3D images. In order to overcome these problems, a very popular approach is to employ models which incorporate a priori knowledge about mean and variance of shape or grey levels of the structure of interest. These models serve to constrain the resulting segmentation contour to probable shapes as defined by the underlying training data set. The concept of shape priors in segmentation methods has been analysed in section 2.4.

In this chapter, a framework is developed for the integration of the GGM-SSM created in chapter 3 as a shape prior for kidney segmentation. In this new method, prior shape knowledge represented by the GGM-SSM is combined with prior information about typical grey value intensity distributions inside and outside the organ to be segmented. The chapter is structured as follows: First an overview is given about the employment of intensity distribution knowledge in medical image segmentation, and the initial placement problem is explained in section 5.1. In section 5.2, a sound mathematical framework is developed which integrates the GGM-SSM into an implicit level set scheme, and the method is evaluated on the segmentation of the kidney from CT images. In section 5.4, the level set framework is extended to multiple-object segmentation, and the algorithm is applied to hip joint segmentation. The chapter is concluded with section 5.5 where the approach of combining an explicitly represented SSM and an implicitly represented segmentation contour is discussed.

5.1 Initialization

5.1.1 Distribution Models for Prior Intensity Knowledge

Beside the prior knowledge about the shape, knowledge-based segmentation methods often integrate information about the grey value appearance of the organ which are extracted from a training data set. Classical segmentation techniques using SSMs mostly
methods propose the utilization of a priori knowledge about intensity information on
its own [Nain 2007, Andreopoulos 2008] or in combination with boundary detection
[Huang 2004] in order to exploit available image information which generally leads to
methods that are more robust and effective.

In point-based SSMs, a widely-used method is to generate local appearance mod-
els. The first local appearance model was presented by Cootes et al. [Cootes 1993]
who proposed to sample intensity information around each landmark in normal direc-
tion. This is done for all observations in the training data set in order to determine
mean value and principal modes of variation of grey value appearance over the corre-
sponding landmarks. During segmentation, the intensity model profiles of each SSM
landmark are compared to the current point profile samples of the deformed SSM in
the image in order to optimize the fit. The local appearance models range from simple
Gaussian intensity profile models and Gaussian gradient profile models [Cootes 1994]
to non-linear intensity profile models [de Bruijne 2002] and histogram region models

A local appearance model as described here is not immediately usable for our GGM-
SSM as one-to-one correspondences over the observations are needed in order to extract
statistical knowledge about the grey values at one specific point of the model. Therefore,
a global appearance model is employed which means that a priori knowledge about the
intensity distributions in the regions inside and outside the organ has to be extracted. In
general, an intensity distribution model consists of two probability density functions
which model the occurrence of grey values inside ($p_{in}$) and outside ($p_{out}$) the organ.
A straightforward method is to sample the grey values of organ pixels $x$ in the train-
ing data set and compute a mean grey value $\mu$ as well as a standard deviation $\sigma_g$.
Then the probability of a voxel grey value $g(x)$ to occur inside the organ is estimated
with $p_{in}(g) = \frac{1}{\sqrt{2\pi\sigma_g}} \exp\left(-\frac{(g-\mu)^2}{2\sigma_g^2}\right)$. Then, $p_{out}(g) = 1 - p_{in}(g)$ could directly estimate
the probability of a voxel grey value $g(x)$ to occur outside the organ. However, for
most soft tissue organs neither the organ tissue nor the surrounding tissue belong to
only one tissue class and additionally, noise has to be taken into account. Therefore,
a classification using a mixture of Gaussians should lead to a more reliable model of
intensity distributions. Thus, we take advantage of a pattern classification technique
introduced by Duda and Hart [Duda 1973] which is based on the so-called kernel density
approximation to estimate the point distribution function of a random variable. This
non-parametric method was first proposed by Parzen [Parzen 1962] in order to solve
problems in the field of time series analysis. In short, the method works as follows: For
a given random sample $X = \{x_1, ..., x_n\}$ the value of the underlying but unknown prob-
ability density function $p(x)$ is sought. Using a kernel or window function $\varphi : \mathbb{R}^d \to \mathbb{R}$
with the properties $\varphi(u) > 0$ and $\int \varphi(u)du = 1$, it can be approximated

$$
\hat{p}(x) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{h^d} \varphi \left( \frac{x - x_i}{h} \right).
$$