Application of a Probabilistic Statistical Shape Model to Automatic Segmentation

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Abstract— **In this paper, we propose a method for applying a probabilistic statistical shape model (SSM) to automatic segmentation. We use a point-represented SSM which is based on correspondence probabilities instead of point-to-point correspondences as commonly used. In order to combine the a priori knowledge of the SSM with the image information during the segmentation, we employ a deformable surface whose deformation depends on on the shape prior given by the SSM on the one hand and on the image information on the other hand. We formulate this problem as an alternated minimization of an external energy term integrating the image information and an internal energy term integrating the SSM probabilities. In order to robustify the segmentation, we add statistical knowledge about typical organ intensities. This method is applied to the segmentation of the left kidney in noisy CT images with breathing artefacts and evaluated in comparison to the results of an active shape model (ASM).**

Keywords— **statistical shape model, correspondence problem, deformable model, segmentation**

I. INTRODUCTION

Segmentation algorithms play a major role in medical image analysis, however, due to typical medical image characteristics as poor contrasts, gray value inhomogeneities, contour gaps, and noise the automatic segmentation of many anatomical structures remains a challenge. To overcome these problems, often models which incorporate a priori knowledge about mean and variance of shape and gray levels are employed [1]. However, for segmentation tasks a statistical shape model (SSM) might easily be too constrained as the number of training observations is often too small to represent all probable shape variabilities. To lighten the constraint, several authors proposed deformable models which balance between SSM and image information, e.g. [2, 3, 4]. These SSMs are based on one-to-one point correspondences and contain statistical information about position and gray level of each point. In this paper, we present a first approach to employ a probabilistic SSM based on *point correspondence probabilities* as proposed in [5] to automatic segmentation. The SSM based on correspondence probabilities can be advantageous when dealing with varying shape details and is able to represent non-spherical shapes [6]. Our method employs a deformable model and relies on the alternated minimization of an external energy term representing the search for edges and the minimization of an internal energy term representing the deformation constraint given by the statistical information about the shape. In an experimental evaluation, we apply the new method to the segmentation of the left kidney in noisy CT images corrupted by breathing artefacts which is not an easy task as the intensity differences between the kidney and neighbouring organs as the liver and spleen are very small. To cope with this, several (semi-automatic) approaches integrate a priori knowledge about shape and gray values [7, 8].

II. MATERIALS AND METHODS

We introduce the surface object O which is placed in the image and deformed during the algorithm in order to fit the contours of the structure to be segmented. The segmentation algorithm consists mainly of the minimization of the two following energy terms:

1. $E_{int}(M,O)$ which is described by the difference between the SSM M and the surface object O, e.g. their surface distance.
2. $E_{ext}(O,I)$ which is described by the difference between the surface object O and the image I, e.g. the distance between the surface of the object to the nearest voxel with high gradient magnitude.

$E_{ext}(O,I)$ is the term representing the external energy of the segmentation problem. The deformation of the surface object O is guided by the image information. In turn, the internal energy $E_{int}(M,O)$ has to be minimized in order to ensure that the shape of the surface object is not evolving too far from the 'allowed' shape space of the SSM.

A. Representation of the Probabilistic SSM

In this model, the interest and nuisance parameters are computed in a unified MAP framework which leads to an optimal adaption of the model to the set of observations. The registration of the model on the observations is solved using an affine version of the Expectation Maximization - Iterative Closest Point algorithm which is based on probabilistic correspondences and proved to be robust and fast [9]. The alternated optimization of the MAP explanation with respect to the observation and the generative model parameters leads to very efficient and closed-form solutions for (almost) all parameters. The SSM is explicitly defined by 4 *model parameters* $\Theta = \{M, v_p, \lambda_p, n\}$:

- mean shape $\bar{M} \in \mathbb{R}^{3N_m}$ parameterized by N_m points $m_j \in \mathbb{R}^3$,
- variation modes v_p consisting of N_m 3D vectors v_{pj},
- associated standard deviations λ_p which describe - similar to the classical eigenvalues in the PCA - the impact of the variation modes,
- number n of variation modes.

From the parameters Θ of a given structure, the shape variations of that structure can be generated by $M = \bar{M} + \sum_{p=1}^{n} \omega_p v_p$ with $\omega_p \in \mathbb{R}$ being the deformation coefficients. The shape variations along the modes follow a Gaussian probability with variance λ_p:
$p(\Omega) = \prod_{p=1}^{n} p(\omega_p) = \frac{1}{(2\pi)^{n/2} \prod_{p=1}^{n} \lambda_p} \exp\left(-\sum_{p=1}^{n} \frac{\omega_p^2}{2\lambda_p^2}\right)$.
In order to account for the unknown position and orientation of the model in space, we introduce the random (uniform) rigid or affine transformation T consisting of a matrix $A \in \mathbb{R}^{3\times3}$ and a translation $t \in \mathbb{R}^3$. A mean model point $\bar{m}_j$ can then be deformed and placed by $T \star m_j = A(\bar{m}_j + \sum_{p=1}^{n} \omega_p v_p) + t$. In order to compute the SSM, a Maximum A Posteriori (MAP) estimation of the model parameters and observation parameters is realized which leads to the following unique criterion:

$$C_{global}(\bar{M}, v_p, \lambda_p, T_k, \omega_{kp}) = \sum_{k=1}^{N} \left[\sum_{p=1}^{n} \left(\log(\lambda_p) + \frac{\omega_{kp}^2}{2\lambda_p^2} \right) - \sum_{i=1}^{N_k} \log \left(\sum_{j=1}^{N_m} \exp\left(-\frac{\|s_{ki} - T_k \star m_{kj}\|^2}{2\sigma^2} \right) \right) \right] \quad (1)$$

given a training data set with observations $S_k, \;\; k = 1, \ldots N$. Consequently, the SSM which best fits the given data set is computed iteratively by optimizing the global criterion with respect to all model and all observation parameters. For more details please refer to [5].

B. Computation of the Internal and External Force

The associated surface model O we are using in this deformable model approach is represented by N_o triangulated points $o_i \in \mathbb{R}^3$. During segmentation, an external force F_{ext} and an internal force F_{int} represented as vectors $\in \mathbb{R}^3$ control the deformations of O. The external force on each point o_i is determined by the underlying image information. Generally, the external force $F_{ext}(o_i)$ should attract the point close to positions with high gradient values. Therefore, we evaluate the gradient magnitude of the points lying in normal direction $\vec{n}_i$ and determine voxels of high gradient magnitude as suitable candidates where the surface points should be moved to. However, evaluating the gradient magnitude alone is not a very robust approach. E.g. it would pose a problem in the case of other organs lying close by as their contour might have a higher gradient than the contour of the organ to be segmented. Also, structures inside the organ might show high gradient magnitude. Therefore, we employ an image force term which depends on the value of three different parameters:

1. Gradient magnitude should be great.
2. Distance from o_i to voxel with high gradient magnitude should not excess a given limit.
3. Grey values found on the way to a candidate should be
   - similar to typical grey values the organ if candidate lies outside the current surface.
   - not similar to typical grey values of the organ if candidate lies inside the current surface.

The last distinction is made to ensure that the surface is neither attracted to contour points of organs lying nearby nor attracted to structures that may be present inside the organ. If the overstepped grey values match the typical organ intensities, we amplify the force attracting the surface point o_i to the outside. If not, the force attracting the point to the inside is preferred, for an illustration see figure 2a),b).

We compute $F_{ext}(o_i) = max\{F_{inside}(o_i), F_{outside}(o_i)\}$ with

$$F_{inside}(o_i) = \underset{o_i + k\vec{n}_i}{\operatorname{argmax}} \left((1 - p(\bar{g}|\mu, \sigma)) \frac{|grad(o_i + k\vec{n}_i)|}{|k|^{\frac{1}{2}}} \right) - o_i, \quad (2)$$

for $-r \le k < 0, \; k, r \in \mathbb{N}$ and

$$F_{outside}(o_i) = \underset{o_i + k\vec{n}_i}{\operatorname{argmax}} \left(p(\bar{g}|\mu, \sigma) \frac{|grad(o_i + k\vec{n}_i)|}{|k|^{\frac{1}{2}}} \right) - o_i, \quad (3)$$

for $0 < k \le r, \; k, r \in \mathbb{N}$. μ and σ denote the average grey value and associated standard deviation inside the organs of our training data set. $\bar{g}$ is the average grey value of the points at positions $o_i + k\vec{n}_i$, that is, the average grey value of the overstepped voxels in order to reach the candidate.

The internal force on each point o_i is determined by the probabilistic SSM. Here, we take advantage of the probabilistic formulation of correspondences. First, we minimize the criterion (1) given $k=1$, $S_1 = O_{def}$ with $o_{def,i} = o_i + F_{int}(o_i)$ and determine the optimal T and ω_p in order to match M on O_{def}. Next, we use the EM-ICP algorithm to compute the correspondence probabilities γ_{ij} of all $T \star m_j$ with all $o_{def,i}$ and find the force $F_{int}(o_i)$:

$$F_{int}(o_i) = \sum_{j=1}^{N_m} \gamma_{ij} \left(T \star (\bar{m}_j + \sum_{p=1}^{n} \omega_p v_p) \right) - o_i \qquad (4)$$

where $\sum_{j=1}^{N_m} \gamma_{ij} \left(T \star (\bar{m}_j + \sum_{p=1}^{n} \omega_p v_p) \right)$ is the most probable position according to the SSM. Finally, the force $F(o_i)$ guiding the point o_i is computed by the weighted sum of F_{int} and F_{ext} and we determine $o_{i,new} = o_i + F(o_i)$:

$$F(o_i) = \frac{1}{2} \left(\alpha F_{int}(o_i) + \beta F_{ext}(o_i) \right) \qquad (5)$$

C. Algorithm

The algorithm performs as follows: First, in order to determine the initial SSM deformation parameters Q, we apply an evolutionary algorithm. A random population of shapes is built by generating a random set of normally distributed transformations T_k and deformations Ω_k and using them to deform the mean shape $\bar{M}$. In each iteration, the fittest individuals are selected and T_k as well as ω_{kp} are modified randomly to again generate a random set until a good initial position and shape are found. The fitness depends on the sum of distances between SSM points and the nearest voxel with high image gradient magnitude. For an example see figure 2d). Next, the associated surface object O is registered to the initial SSM by using an affine transformation determined by the iterative closest points algorithm. Then, F_{int} and F_{ext} are computed and the points o_i of the surface object are moved accordingly. In each iteration, the SSM is matched to the current surface object by optimizing the criterion in (1) given $k=1$, $S_1 = O_{def}$ with respect to T and Ω before the SSM forces are computed. This is iterated until O does not change significantly anymore.

D. Experiments

We apply our method to the segmentation of the left kidney in CT images. The CT images are quite noisy, and the quality of the kidney visualization lacks because of breathing artefacts, see figure 2c). The size of the images is $512 \times 512 \times (32-52)$ voxels with resolution $0.98 \times 0.98 \times (2.9-5.0)mm^3$ where the kidney is about $75 \times 60 \times 100mm^3$. The probabilistic SSM for the kidney is built using a training data set of 10 segmented observations (figure 1a)-e)).

As associated surface object we use a random kidney of the training set for which a surface representation was generated. We chose $\alpha = 0.35$, $\beta = 1$, $\mu = 30Hu$, and $\sigma = 20$. Regarding the intensity distribution in the images, we extended eq. (2) by penalizing $\bar{g} \ll \mu$ for $F_{outside}$. We apply the segmentation method to six new kidneys, for some examples see figure 1,e) and f).

III. Results

The segmentation results are evaluated by analyzing surface distance measures between the deformed surface object and the manual segmentation. Additionally, we evaluate the distances between the resulting deformed SSM and the manual segmentation which represents the results of the probabilistic SSM used as an active shape model (ASM). The distance results are depicted in table 1. Some result examples are shown in figure 2e) and f). The mean distances of the new method lie between $1.32-2.17mm$ which seem to be reasonably good results with respect to the strong artefacts present in the images. The values of the maximum distances ($7.02-11.80mm$) are partly due to the region where the urethra and the arteria a renalis connect to the kidney which poses a problem in some cases because of the high grey value variance without clear borders. Some medical experts include those into the segmentation and others do not. Overall, the method seems to successfully prevent the segmentation from leaking into neighbouring organs with high gradient magnitudes and similar grey value intensities, for an example see figure 2f). Furthermore, the results show the advantage of the deformable model over an ASM approach as the mean distances of our method are smaller than the distances obtained when using the SSM directly to segment. However, in two cases the maximum distances of the ASM approach are smaller which means that α should probably be > 0.35 in those cases.

IV. Discussion

We proposed a method to employ a statistical shape model based on correspondence probabilities for automatic segmentation. In a deformable model framework, we alternate a minimization of an external energy term representing the search for edges and the minimization of an internal energy term representing the deformation constraint given by the SSM. We take advantage of the probabilistic formulation of the SSM when computing the SSM forces as each point o_i is drawn to the most probable position with respect to the SSM, no point-to-point correspondences are needed. The new segmentation approach comes to promising results in a first experimental evaluation on noisy kidney CT images with strong breathing

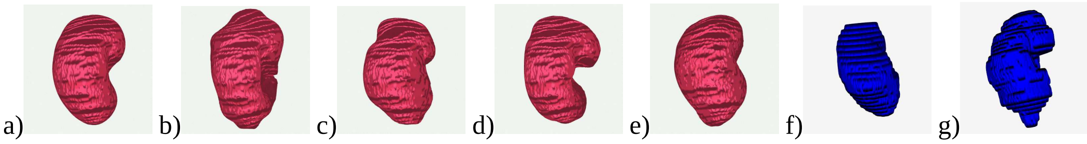

Fig. 1: SSM computed for a training data set of 10 segmented kidneys. (a) shows the mean shape, (b-e) show the mean shape deformed with respect to first and second mode of variation: $\bar{M}-\lambda_1 v_1$, $\bar{M}+\lambda_1 v_1$, $\bar{M}-\lambda_2 v_2$, $\bar{M}+\lambda_2 v_2$. e) and f) show to kidneys to be segmented, results see table 1 (kidneys 3 and 5).

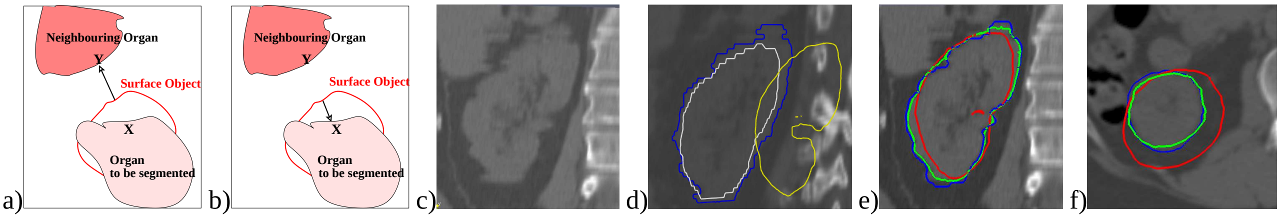

Fig. 2: a) Candidate is determined only by highest gradient magnitude. b) Candidate is determined by a combination of gradient magnitude and evaluation of overstepped grey values lying on the normal. In the case shown, position x is preferred over position y because the overstepped grey values indicate that the surface is positioned outside the organ to be segmented. c) Kidney to be segmented in a noisy CT image with breathing artefacts. d) Initial positioning: SSM contour (yellow), SSM contour after applying the automatic evolutionary algorithm (white), manual segmentation contour (blue). e,f) Segmentation results, manual segmentation (blue), initial surface model (red), resulting surface model (green).

Table 1: *Surface distances in mm between deformable surface and manual segmentation.*

	Kidney 1	Kidney 2	Kidney 3	Kidney 4	Kidney 5	Kidney 6
mean distance deformable model	1.32	1.79	1.97	1.87	2.17	1.46
max distance deformable model	8.06	11.80	10.88	8.31	9.91	7.02
mean distance deformed SSM (ASM)	1.63	2.53	3.25	2.05	2.55	2.69
max distance deformed SSM (ASM)	7.34	13.57	16.66	7.58	10.11	14.52

artefacts as we find mean distance measures around 2*mm* or lower between the manual segmentation and our deformed surface object. Especially in regions where the kidney lies close to neighbouring organs with similar intensity, the prior information about the shape prevents the surface object from leaking. The comparison with the ASM results show the advantage of the deformable model approach as the less constrained segmentation becomes more accurate. For further evaluation, we need to apply the algorithm to a larger data set of kidney CT images as well as to the segmentation of other anatomical structures with higher variabilities as e.g. the liver.

Acknowledgments

The kidney data and segmentations were kindly provided by the department of Computer Science, UNC, Chapel Hill.

The work was supported by the German Research Foundation (DFG, HA2355/7-1).

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