Fully automatic segmentation and evaluation of lateral spine radiographs

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Abstract. A shape model for fully automatic segmentation and recognition of lateral spine radiographs has been developed. The shape model is able to learn the shape variations from a training dataset by a principal component analysis of the shape information. Furthermore, specific image features at each contour point are added into models of gray value profiles. These models were computed from a training dataset consisting of 62 manually segmented lumbar spine images. The application of the model containing both shape and image information is optimized on unknown images using a multi step simulated annealing search. During optimization the shape information of the model assures that the segmented object boundary stays plausible. The shape model was tested on the 62 images using the leaving one out paradigm.

1 Introduction

In clinical routine radiographs of the spine are often applied for the diagnosis of damaged posture or other injuries affecting the vertebrae of the spine. The diagnosis includes the detection of geometric measured values like angles between the vertebrae or the intervertebral disc height. Measuring these values is a time consuming and error prone task for physicians. Therefore, automatic computation of these values is of great interest. However, before an automatic extraction of the desired values from the spine model can be executed, accurate segmentation of the lumbar spine has to be performed. Difficulties arise concerning the quality of the medical images in all day clinical routine from various aspects: superpositions of bones (pelvis), air (bowels), or fatty tissue (obese patient) degrade image information considerably, projection distortion of two dimensional images of the vertebra causes different and varying lines on the bone body.

For these reasons classical methods of image segmentation are insufficient. Therefore we use a knowledge based segmentation technique based on the Active Shape Model (ASM) approach from Cootes et al. [1]. Previous approaches require manual placement of the starting position of the model [2]. This task is compensated by a multi step simulated annealing search method. Beyond, other improvements were applied to the original Active Shape Model approach to achieve higher segmentation accuracy [3].

2 Methodology

The whole approach divides into the generation of a training dataset of contours, the computation of flexible shape and gray value models, and their optimization.

The training dataset for both kinds of models, shape and gray value models, consists of manually drawn shapes. Each object shape has a constant number of landmarks located at the regions of interest, which are usually the parts of the contour with the highest curvature. Figure 1 illustrates the structure of the training dataset including the landmark points. Usually the manually drawn shapes have a differing number of contour points, but the computation of the model requires the same number of points for each element of the training dataset. Therefore, the contours are interpolated equidistantly between the landmark points.

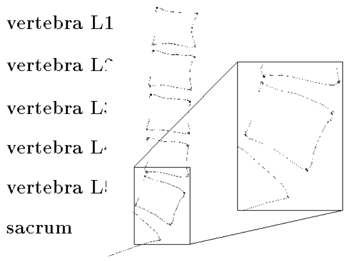

Fig. 1. Training example of a spine with landmark points marking the four corner points of the vertebrae.

2.1 Building the Model

The interpolated shapes also contain, beside the real shape variations, affine variances. For better control over the model behavior, it is profitable to separate the affine variances from the real shape variations. Since all shapes have an equal number of points, they can be aligned towards the mean shape using a least squared error method.

Each element of the aligned training dataset can be expressed as an $2n$-dimensional vector $\mathbf{x} = (x_1, y_1, \ldots, x_n, y_n)$. Suppose now the elements of the training dataset form a cloud in $2n$-dimensional space a Principal Component Analysis (PCA) can be used to approximate any of the original points with fewer than $2n$ parameters. The main aspect of this computation step is to reduce the dimensionality of the data significantly to model the shapes of the training set. Contour models using this kind of contour representation are also known as Point Distribution Models (PDM).

At this point we are able to compute a flexible shape model efficiently using a comparatively small number of parameters. But the shape model so far is only able to express shape characteristics of the training dataset. For an optimization of the model on unknown image material typical image features must be extracted from the images the training dataset was generated from. A strong feature is always the edge information of the objects. But gradient information itself is far too weak for a proper segmentation, because inside and outside of the object cannot be distinguished anymore.

Therefore gray value profiles are extracted from the images showing characteristic variations. To be independent of the varying exposure of the images the profiles are normalized. The computed normalized profiles are perpendicular to the shape contour and always have the same size. For each point of the shape model a gray value profile model is computed analogous to the computation of the shape model. The image structures may vary in different parts of the contours of the object. Therefore it would be very inappropriate to compute one general profile model for the whole object.

2.2 Optimization

For optimization a simulated annealing search technique is used. Four affine parameters and n model parameters must be optimized. Reasonable boundaries of the affine parameters are extracted either from the image dimensions and the affine variabilities in the training dataset. The boundaries for the model parameters are also estimated from the shape variations of training dataset. Each parameter can take different values in its interval, which are defined by a step size for each parameter.

The elements of the search space are defined by the values of the $4 + n$ parameters of the model. Each element has exactly $2(4 + n)$ neighbors, which can be computed by decreasing or increasing an parameter by its step size. Each element of the search space defines a shape located in the image frame. It is obvious that the energies of two neighboring elements of the search space do not differ significantly. Considering all elements of the search space they form an energy mountain profile, wherein the deepest valleys are the regions which correspond to the global minimum.

Simulated annealing can be viewed as a local search through that mountain profile enriched by a kind of randomized decision choosing whether to leave local optima in order to find better solutions.

The optimization is performed in three constitutive steps. At first a model consisting of 5 vertebrae and the sacrum is optimized on a down-sampled image of size $\frac{1}{16}$. This leads to a rough estimation of the position and major shape variations of the model. Thereafter the model is broken apart into three smaller models consisting of two vertebrae each. The segmentation information of the previous step is taken as an initialization for this optimization which is running at a scale of $\frac{1}{2}$. Finally shape models of each vertebra are optimized on the original image. In each step the allowed variation of the models is limited dependent on the segmentation result of the previous step. Furthermore the effect of breaking the model apart successively into smaller models leads to a decrease of shape variation in the training sets, which produces smaller search spaces for the simulated annealing optimization.

3 Results

The algorithm was tested on 62 unknown spine images of average image quality using the leaving-one-out paradigm. That means the different models were computed from the 61 remaining contours and the actual spine contour was taken as a reference contour to evaluate the result. Figure 2 shows a typical result after application of all optimization steps. For comparison the reference shapes are also displayed.

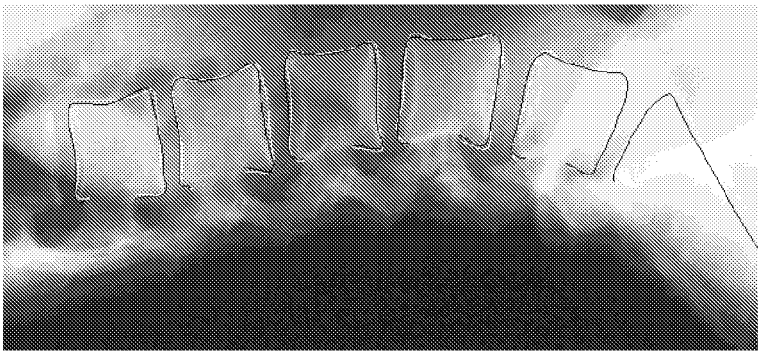

Fig. 2. Final segmentation result (white contour) of x-ray images together with the manual reference shapes (black contour).

3.1 Evaluation

The validation of the result shapes is performed by comparing them with manually drawn reference shapes. A number of different measures were extracted from the segmentation results. The mean, minimum, and maximum percentage cover $\bar{c}$, c_{min}, c_{max} of the shapes, the mean distances between the shapes $\bar{d}_S$ and the landmarks $\bar{d}_L$ in millimeters, and the minimum and maximum distances between the shapes $d_{min,S}$, $d_{max,S}$ and the landmarks $d_{min,L}$, $d_{max,L}$ in millimeters.

The maximum distances $d_{max,S}$ and $d_{max,L}$ were computed as the largest of the individual distances between result and reference shape. They quantify the overall localization quality by the largest occurring discrepancy. Whereas $\bar{d}_S$ and $\bar{d}_L$ are a measure for precision of the local delineation of shapes and landmarks respectively. Furthermore the mean percentage cover $\bar{c}$ can also be taken as a measure for the overall detection accuracy. Table 1 shows the results for each vertebra and the spine as a whole in detail.

Table 1. Final results of spine segmentation. The distances and their standard deviations are specified in millimeters.

	$\bar{c}$ $\mu \pm \sigma$	c_{min}	c_{max}	$\bar{d}_S$ $\mu \pm \sigma$	$d_{min,S}$	$d_{max,S}$	$\bar{d}_L$ $\mu \pm \sigma$	$d_{min,L}$	$d_{max,L}$
Vertebra L5	92.0 ± 4.2	79.3	97.3	1.28 ± 1.76	0.0	13.11	3.05 ± 2.41	0.15	13.51
Vertebra L4	91.9 ± 3.6	82.5	97.1	1.28 ± 1.68	0.0	12.90	2.82 ± 2.09	0.13	10.71
Vertebra L3	92.2 ± 3.7	82.8	97.4	1.43 ± 1.92	0.0	14.08	2.49 ± 1.73	0.08	10.71
Vertebra L2	91.4 ± 4.0	81.4	96.9	1.53 ± 2.05	0.0	15.01	2.55 ± 2.22	0.08	13.48
Vertebra L1	91.4 ± 4.4	72.2	97.1	1.46 ± 1.95	0.0	22.28	2.94 ± 2.85	0.21	20.69
Sacrum	79.8 ± 9.9	48.0	95.1	2.06 ± 2.95	0.0	33.18	5.19 ± 4.16	0.47	21.78
Spine	89.8 ± 7.0	48.0	97.4	1.51 ± 2.03	0.0	33.18	3.17 ± 2.62	0.08	21.78

4 Conclusion

We have presented a multi-step approach for the segmentation of the lumbar spine. A typical problem of deformable model adaption is the determination of the starting position. If the starting position is not close enough to the object, the algorithm runs the risk of being attracted to false features. Considering the spine with its ability to be more or less twisted a placement of the initial contour using only affine parameters is far too weak. Hence we use a simulated annealing search, which enables us to integrate a variable amount of model parameters into the search process to acquire a satisfying starting shape. Furthermore the adaption by breaking the spine model apart into separate models improves the segmentation accuracy significantly.

In summary the segmentation accuracy of the most significant parts of the shapes, the landmarks, is measured by a distance of 3.17mm with a standard deviation of 2.62mm. But these results can only give an estimation about the quality of the segmentation because the evaluation of each snake was only performed with a single manually drawn snake. Hence an evaluation with a set of contours of each snake manually drawn by different users would be practical. However the results show that this approach is able to provide fully automatic spine segmentations of a subjective satisfying quality.

Finally the presented approach can be easily applied to other segmentation tasks. Even an application in three-dimensional medical imaging is possible [4].

References

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