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Knowledge-based femur detection in conventional radiographs of the pelvis

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Abstract

In this paper we present a knowledge-based femur detection algorithm. The algorithm uses femur corpus constraints, Canny edge detection and Hough lines. For optimal femur template placement in the local area we use cross-correlation. The segmentation itself is done with an optimized active shape modeling technique.

Using the knowledge-based technique we have located 95% of the femur shapes of $N = 117$ X-rays. From those 83% of the target femur shapes have been segmented successfully (point-to-point error: $\sim$14 pixels, point-to-boundary error $= \sim$9 pixels).

Keywords: Femur detection; Hough lines; Template initialization; Femur segmentation; Active shape modeling

1. Introduction

Osteoporosis is a severe metabolic disease of skeletal system, which leads to a substantial restriction in mobility of patients as well as to skeletal fractures. Beside the vertebral spine and the distal radius, femoral neck is particularly affected by osteoporosis.

The treatment of neck fractures depends on the type of fracture as well as on bone quality. Commonly, the estimation of bone structures of the injured patients is routinely performed by X-rays of the pelvis, if a traumatic injury of the pelvis or the femoral neck is suspected. The diagnosis is done by a radiologist or a specialist in traumatology. The correct diagnosis depends on the quality of the X-ray and on the experience of the physician. A technical support for the requirement of osteoporosis analysis is the automatic localization of femur in order to place the regions of interest on plane radiography.

The major problem is the exact delineation of the femur shape, especially considering the contrast, the gray scaling and the position. Moreover, due to the superposition of overlapping abdominal structures in plane radiography and variations in shape and position of the patient, locating and exact segmentation of the femur is a challenging task. In case of this, experience in interpretation of X-rays is necessary. Manual shape extraction is time consuming, subjective and error prone, so it is not practicable in clinical routine.

The first main challenge is to find automatically the femur structure in a hip overview X-ray. The easiest way is to pose manually a template close enough to the target shape, as mentioned by Behiels et al. [1]. We, however, propose an automatic knowledge-based location technique using an edge-based technique and Hough lines [2,3]. The optimal location for initializing the template is found by cross-correlation.

After successful template initialization an optimal segmentation technique should be applied. Standard low level segmentation techniques, relying especially only on pixel intensities, often generate incorrect object delineations. One idea to handle this problem is to incorporate a priori information of shape in the segmentation process. Based on that, the most promising method described so far, has been published by Behiels et al. [1]. This method is based on active shape models (ASM) [4,5] and shows a success-rate by approximately 70%.

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One of the main causes for the missing 30% seems to be the disregard of variations in position. For improvements Behiels et al. suggested an enhancement of the model with these variations. However, the risk of getting an unspecific model may be increased by the mixture of the independent variations in shape and position.

The application of ASM in plane radiography requires high performance of the algorithm. An essential criterion is the optimal shape model for covering the main shape variations. This depends mainly in correct corresponding landmark-points between different objects. One may use characteristic points, which are carefully chosen by an expert, to make sure that drawn points in different shapes are identical. These points may refer to the same anatomical landmark position on the object boundary, but may be error prone and subjective. This may only work for some characteristic points and a small number of subjects. To solve this problem, Behiels et al. proposed a bootstrap procedure to construct the training set of manual segmentation. We use a prior optimized shape model, constructed in using the minimum description length method (MDL) proposed by Davies et al. [6].

The ASM segmentation method tries to find the shape and the pose parameters of the PDM generated contour, which fits the object boundary to an image in best quality. When target points have been determined for all ASM points, the pose and shape parameters of the ASM contour are updated, so that the new ASM shape fits the target points as closely as possible. This process is repeated until convergence or a limit of iterations is reached. In the standard technique target points are determined independently for each contour point and may produce occasionally outliers that pull the contour away from the true boundary position that cannot be corrected during further iterations. This may happen especially due to lack of contrast or when multiple edges are presented nearby. Behiels et al. propose a regularization term before updating as an effective method. In this work we use a profile scale space method.

The key point for successful segmentation, however, depends on the initial placement of the template. If the initial position is too far away, the correct femur contours will never be reached. Behiels et al. have mentioned an initial instantiation of the ASM contour sufficiently close to the true object boundary contour. Within this work we try to quantify the distance of the template placement from the target shape for successful segmentation.

In Section 2 we present the idea of the knowledge-based location technique and summarize the optimized ASM technique for the femur segmentation on hip plane-radiography. Experiments evaluating the accuracy of our method are presented in Section 3. Benefits and further problems are discussed followed by a conclusion.

2. Methods

2.1. Data

The database consists of 197 conventional plane-radiography of the pelvis, obtained from the Department of Radiology of the Medical University of Innsbruck. They have been performed in clinical routine, the major of them with the diagnosis of a hip fracture after trauma. All images have a size of 2320 pixels in x-direction and 2828 pixels in y-direction. The pelvis has been symmetrically imaged with a homogenous brightness including both hip joints, trochanter major and minor.

For further processing the original images are smoothed using a median filter and a contrast enhancement is gained through histogram equalization.

The segmentation of 200 selected femur shapes from either both or one side of the complete database has been done manually and has been supervised by a clinical expert. Each femur shape consists of 256 contour points.

2.2. Statistical shape model

In order to find the femur shape structure in a hip overview we need an optimal template incorporating structure knowledge. This is obtained from an optimal statistical shape model. Furthermore we need to incorporate a statistical model of regular shape variation in the ASM method.

2.2.1. Contour pre-processing

Using the rough segmented shape, we get a major problem in construction of corresponding points, especially at the femur corpus, because of the free ends. To select the lower end of the trochanter minor as the contour beginning will not work for all X-rays. The trochanter minor is not clearly visible in all datasets, especially due to possible rotation. Fig. 1 shows two examples. On the left side a high quality X-ray with the trochanter minor, on the right side a low quality X-ray which does not show trochanter minor.

We solve this problem by calculating the maximal interior distance of the femur shape. We calculate the distance from that point to the center of the femur head. The same distance is applied to the femur corpus and provides an ideal criterion for cutting the open femur ends. Based on that criterion we provide the base shapes of 200 femurs for the generation of the statistical shape model.

2.2.2. Construction of the prior shape model

After we have generated the prior femur shapes, we align the set of corresponding points to one another with respect to translation and rotation. This is accomplished using an iterative algorithm based on the Procrustes method [7]. After alignment, there is still a substantial amount of variability of each point. For a compact description this variability as a prior model, Cootes and Taylor developed the point distribution model (PDM), described as follows:

The N aligned femur shapes $Y_1, Y_2, \ldots, Y_{\mathrm{N}}$ in the model space, where $Y_i = (x_{i0}, y_{i0}, \ldots, x_{in-1}, y_{in-1})^{\mathrm{T}}$ is a $2n$-dimensional vector describing the coordinates of n points from the ith shape, the mean femur shape, Y_{m}, is defined as

$$Y_{\mathrm{m}} = \frac{1}{N}\sum_{i=1}^{N} Y_i. \tag{1}$$

Fig. 1. The X-ray on the left side shows a hip overview with optimal femur contrast and a clear visible trochanter minor, whereas the image on the right side does not.

A covariance matrix, S, is computed by

$$S = \frac{1}{N-1}\sum_{i=1}^{N}(Y_i - Y_\mathrm{m})(Y_i - Y_\mathrm{m})^\mathrm{T}. \tag{2}$$

The eigenvectors corresponding to the largest eigenvalues of the covariance matrix describe the most significant modes of variation. Because almost all of the variability in the model can be described using these eigenvectors, only k such eigenvectors are selected to characterize the entire variability of the 200 femur shapes. The numbers of eigenvectors are chosen, so that the model represents 98% of the whole variance of the data.

Using a principal component analysis (PCA), any shape Y in the training set can be approximated by

$$Y \approx Y_\mathrm{m} + Pb, \tag{3}$$

where $P=(p_1, p_2, \ldots, p_k)$ is the matrix of the first k eigenvectors, and $b=(b_1, b_2, \ldots, b_k)^\mathrm{T}$ is a vector of weights, referred to shape parameters. The change of shape can be made by varying b accordingly. Limits on the values of b are imposed to constrain the actual amount of deviation from the mean shape.

2.2.3. Model optimization

Further processing with the statistical shape models requires an important attitude: the model should only generate a pattern of 'legal' variations in the shapes [8]. Therefore, it is important to establish the 'correct' correspondence; otherwise an inefficient parameterization of shape can result, affecting the compactness, specificity and generalization ability of the model.

One way to generate an efficient parameterization of this variability is to use the MDL, proposed by Davies et al. [6]. This method—in the spirit of Occam's razor—manipulates corresponding points on optimizing the objective function, which lead to the MDL of the PDM built on the training set. We applied the MDL method, using a Matlab code, based on the source code provided by Thodberg [9].

2.3. Knowledge-based femur detection

The segmentation result depends mainly on the initial position of the starting shape. For successful segmentation, an adequate placement of the template—the mean of the statistical shape model—in the X-ray overview is required. We propose an automatic template placement based on specific structures of the femur shape, e.g. size, shape and location. This knowledge can be derived through a variety of low-level segmentation algorithms. We use the Canny edge detection followed by Hough lines including local constraints in a hip overview.

2.3.1. Femur corpus detection

The femur corpus is a characteristic anatomical structure in a hip overview X-ray. This anatomical object is represented by two roughly vertical parallel lines with a high gradient in the lower region of the X-ray, one on the left side (left femur) and the other on the right side (right femur), as shown in Fig. 2(a).

To detect these specific lines we have used the Canny edge detection algorithm, see Fig. 2(b) [2]. We excluded lines with low gradient magnitude, with horizontal edge orientation (deviation $= \sim 45°$), vertical lines crossing 75% of the whole X-ray, lines in the upper part and small line segments from further investigations. If these constraints are applied as a filter on the previous extracted edges, the number of potential edges generated for the femur corpus is greatly reduced. In a following step we detect parallel lines using Hough lines method [3] within that region.

These specific marked edges, see Fig. 2(c), which belong to the crest-lines of the femur corpus, provide essential information for a pre-pose of the template. The distance between the neighboring lines provides information about the width of the femur—the scaling parameter for the femur shape. The direction of the lines provides the alignment of the femur template as a first rough initialization, as shown in Fig. 2(d).

2.3.2. Position optimization

For optimal placement of the template we use the mean structure along the mean femur shape (see Fig. 3). This information is matched in the local search area starting from the previous mentioned rough initialization along the femur direction using translation and scaling. For every possible pose we calculate the cross-correlation coefficient r (Eq. (4)) between the gradient of the template structure g_t and the local area gradient

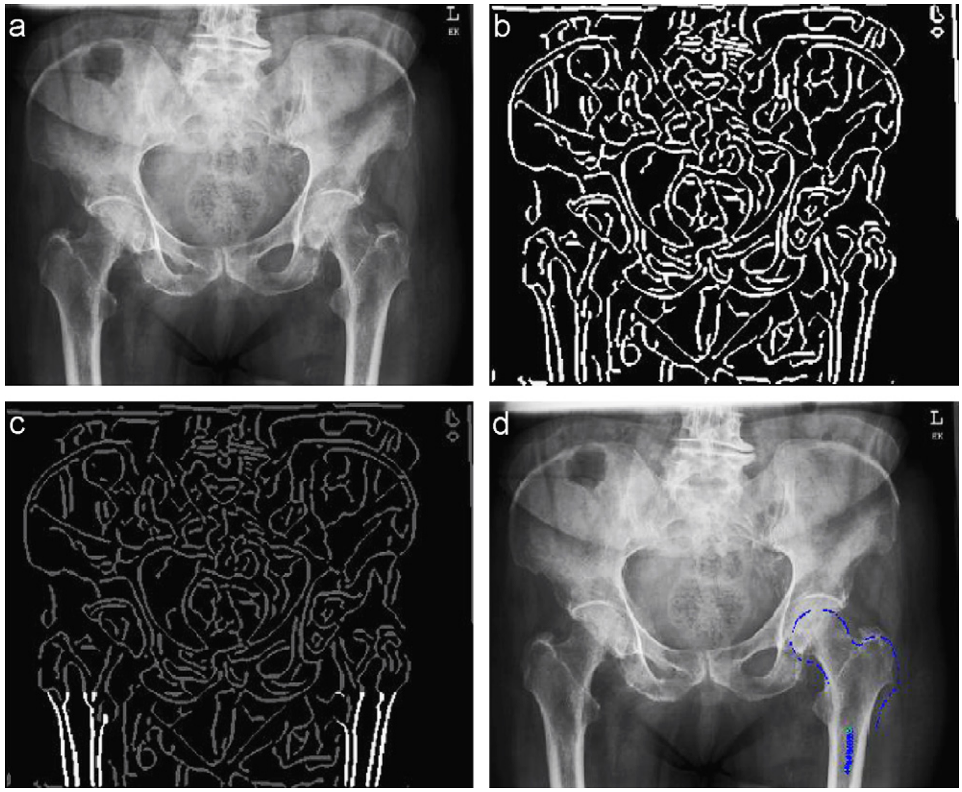

Fig. 2. The automatic placement of the femur template based on characteristic anatomical structures of the femur corpus. The original X-ray is shown on the upper left side (a), all edges are shown in the upper right (b), the object specific edges are shown on the lower left side (c) and the final template placement on the lower right side (d).

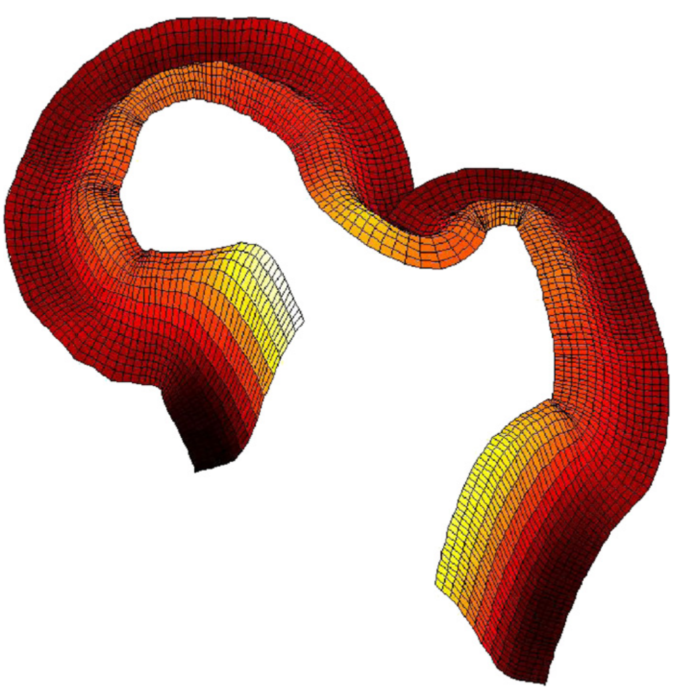

Fig. 3. This figure shows the height coded contour profile along the mean femur shape.

along the posed template shape g_s on the X-ray using 64 positions along the shape. The pose with the highest correlation coefficient r reveals the proper parameters for optimal placement of the template

$$r = \frac{\mathrm{cov}(g_t, g_s)}{\sigma_{g_t}\sigma_{g_s}}. \tag{4}$$

2.4. Segmentation

With a given optimal prior shape model and an optimal initialization we start the segmentation using an optimized ASM method, originally proposed by Cootes and Taylor [4,10].

However, the standard ASM technique will not work for weak contrast or when multiple neighboring edges are present. During optimization, new target point positions, that fit optimally the image model, are searched in a local neighborhood. Single points, probably outliers, may drive away the shape and further iterations will never find the optimal shape in the image. To avoid this, Behiels et al. have suggested the use of a regularization term of target point configuration. We apply a profile scale space method, similar to the method, proposed by Ho and Gerig [11].

2.4.1. Profile scale space

The key feature is that profiles are not blurred across the image but along the shape boundary. The profile of the image across the object boundary may vary significantly from one portion of the boundary to another. Some portions of the boundary might not even have a visible contrast, in which case the shape prior is needed to define the contour. With a scale-space defined on the image profiles along the object boundary, we sample features from the scale space in a coarse to fine fashion. In this way we regularize potential outliers in the coarser resolution by the mean value of that region. We built a statistical model on the multi-scale tree of features. In our implementation we use 256 samples at the finest scale, down to 16 at the coarse scale, in total five profile scale space levels. Fig. 3 gives an example of the boundary profile structure of the finest level (256 points) for the mean shape.

2.4.2. Multi-resolution ASM procedure

To improve the efficiency and robustness of the algorithm, we have implemented a general multi-resolution framework as proposed by Cootes et al. [12]. This involves first searching for the object in a coarse image, then refining the location in a series of finer resolution image. This leads to a robust algorithm, which may not be stuck on the wrong image structure.

For each image the Gaussian image pyramid is built [13], providing sub-sampled images of the base image. During training we build statistical models of the gray-levels along normal profiles through each point at each level. We use the same number of pixels in each profile model, regardless of level. While the models at the coarser level represent more of the image, the finer level presents more details in the close enough of the shape boundary. At the coarse level this allows quite large movements, providing a good global solution, at the finer resolution we need only modifying this solution by small amounts.

In this multi-resolution framework we have included the profile scale space method in every resolution, which is mentioned above.

2.5. Fit quality

The ASM method is applied to each left femur of the hip overview in the database, where the according femur shape exists ($N = 117$). Many of the right femurs were fractured or replaced with an implant. The obtained segmentations are compared with the manual segmentations by the point-to-point error ($E_{\text{pt–pt}}$) and by the point-to-boundary error ($E_{\text{pt–bd}}$). The point-to-point error is defined as the distance in pixels between corresponding points. The point-to-boundary error is the distance in pixels between automatically segmented contour and the closest point to the manually delineated femur contour.

2.6. Software parameters

The knowledge-based feature detection is done on a rough image resolution (level = 4). The local optimization for translation is within a range of double the femur corpus width and the scaling varied between 0.9 and 1.1 multiplied with the detected femur width.

Each femur shape consists of 256 data points. The optimal statistical shape model using MDL is generated within 25 passes using free ends with a relative precision of 0.25%.

The ASM method is applied in the multi-scale approach using 3 iterations, 5 levels, 5 iterations in each level and 3 iterations in each profile scale space. The profile length for searching of the local structure is 17. The model impact is 95% in the coarse level, decreasing a step of 3% in every level, down to 80% in the finest level.

The whole software pipeline is implemented on a windows workstation using Matlab software.

3. Results

In this section we summarize the results of optimal femur model generation, the successful knowledge-based femur detection and the exact contour delineation using optimized ASM segmentation technique on X-ray hip overviews.

3.1. Statistical shape model

We have generated an optimal femur shape model using the MDL approach, based on 200 supervised segmented femurs. The aligned femur shapes, after pre-processing, are shown in upper left side of Fig. 4(a). The PCA distribution for the two main variations is shown in the upper right side (b). The mean femur shape is shown on the lower left side (c), and the variance of the data in the ith principal mode of variation concerning the impact to the statistical shape model is shown in the lower left side of Fig. 4(d). The first five main components cover a shape space of more than 83%, and the first 10 cover a shape space of more than 95% of the model variation.

Fig. 5 demonstrates the variations due to the first three modes for ± 3 standard deviations (σ). The PCA-based decomposition of complex individual variations reveals meaningful and characteristic modes of variations that can be described as follows: the first mode describes the elongation of the femur neck and the second mode reveals in variations due to femur head angulations. The third component shows variations of the trochanter major.

3.2. Knowledge-based femur detection

The knowledge-based template initialization has been successful in 112 samples ($\sim$95%) out of $N = 117$ cases. All the failed template initializations, with less than 50% overlapping between the template and the femur shape, have been excluded from further processing. The point-to-point and point-to-boundary errors ($E_{\text{pt–pt}}$, $E_{\text{pt–bd}}$) between the manual segmented and the initial positioned shape are given in Table 1.

3.3. ASM segmentation

After placing the template at the right location on the hip overview, we apply successive coarse to fine segmentation algorithm using both scale pyramids.

We also calculate the point-to-point and point-to-boundary error-distance ($E_{\text{pt–pt}}$, $E_{\text{pt–bd}}$) between the manual segmented and the ASM segmented femur shapes. The results for the errors are given in Table 1. Exact delineations are characterized by a low error, whereas not exact ones have a high error, especially in the region of the femur head and neck, which is not useful

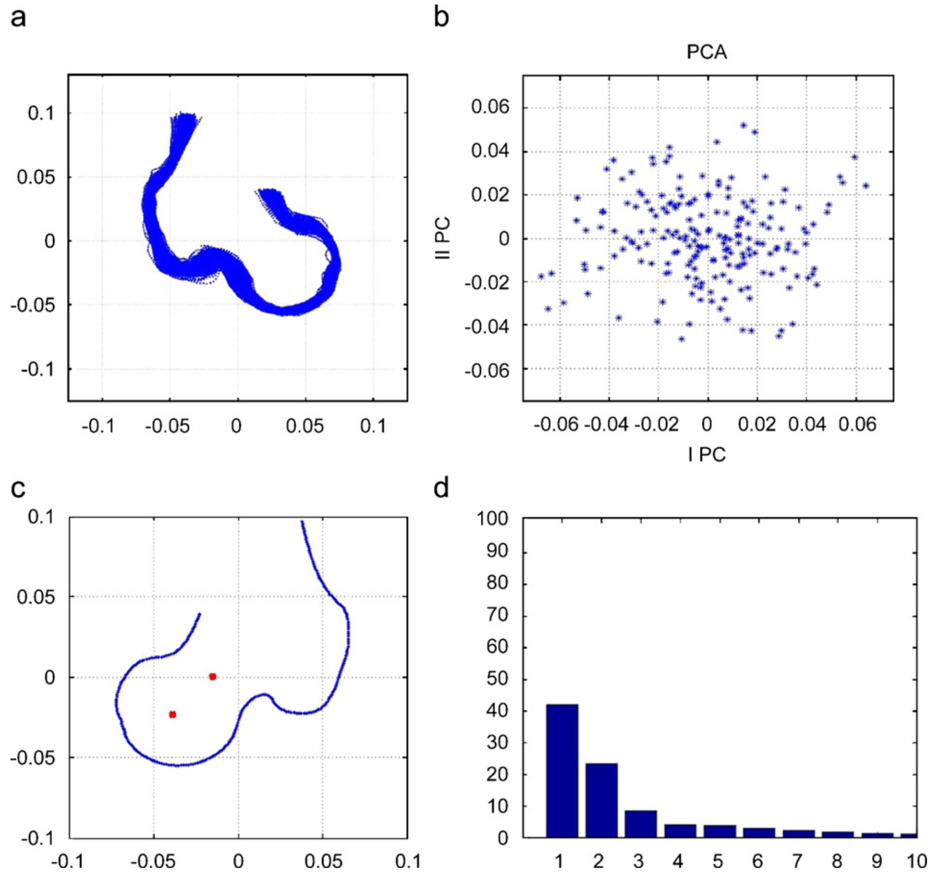

Fig. 4. The 200 aligned femur shapes are shown on the upper left side (a), the resulting distribution of the PCA for the two main variations are shown in the upper right (b). The mean shape, including the center of the femur head and the thinnest location of the femur neck are shown on the lower left side (c) and the eigenimpact of the PCA on the lower right side (d).

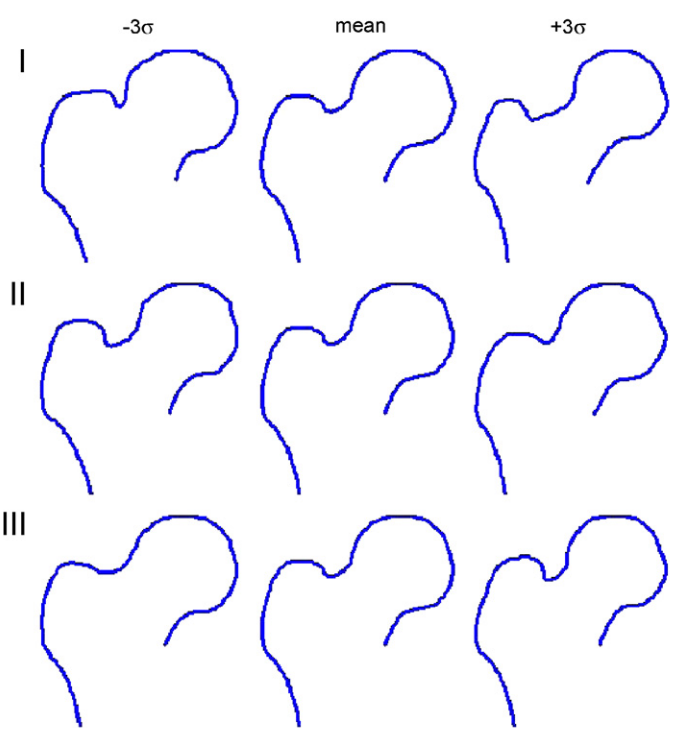

Fig. 5. This figure presents the shape variation of the statistical shape model for the three main variations: I, II, and III. The mean shape is given in the middle, with the standard deviations ($\pm 3\sigma$) on the left and right side.

Table 1
Summary of the errors (E_{pt-pt}, E_{pt-bd}) between the knowledge-based placed template and the manual segmented femur shapes

Knowledge-based placed template							
	N	Init vs. Ideal		ASM vs. Ideal		%[a]	%[b]
		E_{pt-pt}	E_{pt-bd}	E_{pt-pt}	E_{pt-bd}		
All	117					100.00	
Init	112	52.48	30.29	20.44	12.39	95.73	100.00
Exact	93	47.10	29.02	14.45	9.10	79.49	83.04
Not exact	19	78.87	36.45	49.76	28.48	16.24	16.96

The error is calculated between the successful posed template and the segmented femur contour (Init vs. Ideal), and between the ASM and ideal femur contour (ASM vs. Ideal). The errors are given for all right femur shapes (All), divided in exact and not exact segmentations.

[a]The percentage of successful segmentation is given with respect to all initial X-rays (%).

[b]The percentage of successful segmentation is given with respect to all successful initialized placed templates (%).

for further medical use. About 83% of the remaining shapes have been found exactly within a range of $E_{pt-pt} = 14.45$ pixels or $E_{pt-bd} = 9.10$ pixels, whereas in 17% the exact delineation failed. Examples of successful and failed femur segmentations are given in Fig. 6.

Fig. 6. This figure shows examples of segmentation results using the applied pipeline. The dark contour shows the initial position given by the knowledge-based template initialization and the light contour is the final segmentation result. Four optimal segmentations are shown in the upper part of the image with the following errors: $E_{\text{pt–pt}} = 12.24$, $E_{\text{pt–bd}} = 5.55$; $E_{\text{pt–pt}} = 8.2$, $E_{\text{pt–bd}} = 5.99$; $E_{\text{pt–pt}} = 4.39$, $E_{\text{pt–bd}} = 3.85$ and $E_{\text{pt–pt}} = 16.35$, $E_{\text{pt–bd}} = 9.13$. However, the segmentation failed in the two lower shapes ($E_{\text{pt–pt}} = 25.31$, $E_{\text{pt–bd}} = 18.23$ and $E_{\text{pt–pt}} = 42.91$, $E_{\text{pt–bd}} = 18.81$).

3.3.1. *Error distance for successful segmentation*

To answer the question of how close the template should be placed to have a successful segmentation, we have calculated the distance between the posed template and the manual segmented femur contour based on two characteristic points: femur neck and femur center.

Fig. 7 shows two histograms concerning the mean distance of the characteristic points from the template to the target points: the upper one, when the segmentation has been successful, the lower one, when the segmentation failed. With a decreasing distance the probability of successful segmentation increases except for some shapes. For comparison only, the mean distance between the femur center and neck has been about ~190 pixels for all shapes.

3.4. *Software performance*

The whole software pipeline is implemented in Matlab. The MDL approach for the 200 femur shapes takes about 3 days on an Intel Pentium machine (2.0 GHz), this procedure, however, has to be done only once.

The computation time for the whole pipeline is ~15 min, ~5 min for feature detection, and ~10 min for each ASM procedure.

4. Discussion

Within this work we have investigated the possibility of automatic detection of the femur shape followed by exact contour delineation in conventional X-ray of the pelvis. Three major problems have to be solved: a generation of a robust shape prior and structure, a plausible and robust femur detection technique and an adequate segmentation procedure.

4.1. *Statistical shape model*

We have generated an optimal shape prior based on 200 femur contours. In this context the pre-processing for the adequate open end treatment has been a milestone for further optimization. This idea may be applied furthermore to similar bone shapes and even to 3D objects.

The MDL technique provides a robust statistical shape model concerning generality, specificity and compactness. The most important information is captured within a minimum number of eigenvalues respective eigenspaces.

A shape prior, which is based on 200 contours, is meaningful. The first two components describe specific variations, which also indicate a good compactness. This model provides a good base for the ASM segmentation technique, but also for other statistical analysis, e.g. shape comparison between right and left femur concerning the contour and/or the gray values in between, respectively, the bone structures.

4.2. *Knowledge-based femur detection*

The knowledge for detecting the femur shape seems sufficient, well defined and robust. The drop out quote depends mainly on the following three factors: First, we could not detect the sharp lines of the femur corpus especially due to low contrast. Second, the optimization technique trapped in a local minimum. And third, the optimization is up to now only based on rigid registration using translation and scaling.

An essential improvement for initial femur detection may be achieved using other constraints or methods, e.g. in the frequency domain, and/or non-rigid registration. To optimize and

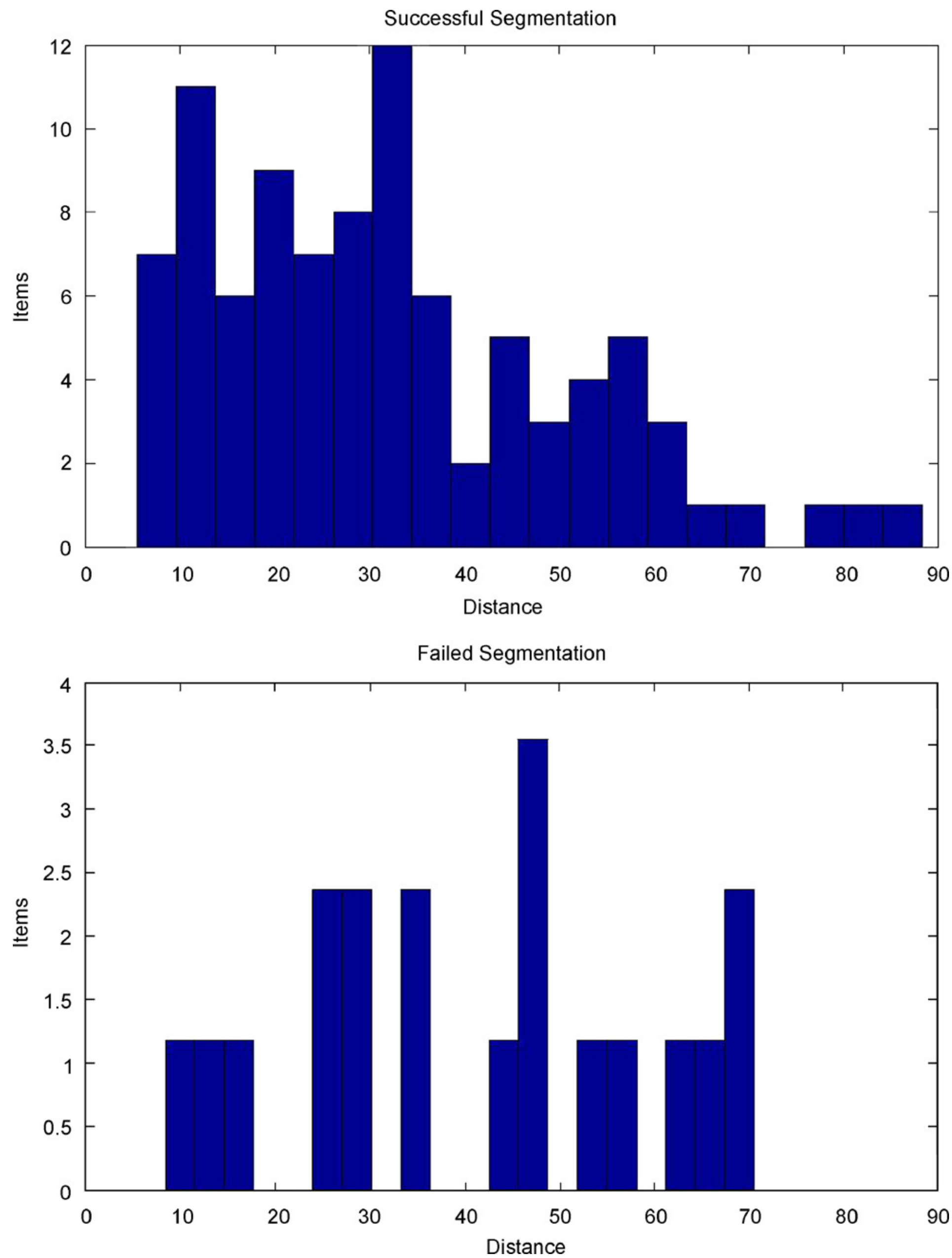

Fig. 7. This figure shows two histograms concerning the mean distance of the characteristic registration points: femur neck and femur center. The upper image shows the distance concerning the successful segmentation, whereas the lower image shows the distance for the failed segmentations.

avoid local minima, the method should be applied to the scale space.

4.3. ASM segmentation

The success of segmentation depends mainly on the initial template position and the algorithm itself. Within this work we have also tried to find out the maximal displacement of the initial contour for exact segmentation.

The proposed initial placement is achieved by the knowledge-based technique and provides usual positions close to the target shape. About ∼83% of the adequate posed shape have been successful segmented. The drop out of 17% is based especially on the low contrast of the femur shape itself and local failure due to projection or speckles. Another reason is the misplacement of the template shape.

4.3.1. Segmentation technique

We have applied an optimal coarse to fine segmentation algorithm which allows the successful segmentation of femur shapes in conventional X-rays. The combination of two scale space techniques allows high performance. A maximal number of 225 iterations produce a success rate of 83%. The remaining error has been localized especially in the region of the trochanter major, due to the low contrast of the back part of the trochanter.

To summarize, the segmentation result is reproducible for previous segmented data.

The software pipeline is experimental and due to Matlab has a low performance.

4.3.2. Error distance for successful segmentation

The lower the distance from the target shape, the higher the probability for succeeding in the segmentation. However, we have not yet been able to derive an explicit quantitative number for a successful segmentation, because of several reasons. The distance to the target shape is the most important point, but the relative initial pose to the target shape and the local contrast of the image in the vicinity should not be neglected. However, it seems that all the initialized templates are in the range for succeeding with a distance of less than 90 pixels.

5. Conclusion and future work

This knowledge-based technique provides a promising tool of automatic femur detection in clinical routine measured hip overviews. The segmentation algorithm clearly outperforms presented algorithms in the literature.

Ongoing work is the optimization of the template placement, including other anatomical criteria or using different or hybrid detection methods. An optimal placement should be defined for ideal template placement. The method should be evaluated on unseen shapes and probably on shapes with hip fractures after trauma. Furthermore a quality factor for the segmentation result should be provided.

6. Summary

Osteoporosis is a severe metabolic disease of skeletal system, which leads to a substantial restriction in mobility of patients as well as to skeletal fractures. The correct diagnosis depends on the quality of the X-ray and on the experience of the physician. A technical support for the requirement of osteoporosis analysis is the automatic localization of the femur in order to place the regions of interest on plane radiography.

In this paper we present an automatic knowledge-based femur detection algorithm in conventional X-ray of the pelvis. The algorithm uses specific structures of the femur shape, e.g. size, shape and location. This knowledge can be derived through a variety of low-level segmentation algorithms. We use the Canny edge detection followed by Hough lines including local constraints in a hip overview.

Specific marked edges, which belong to the crest-lines of the femur corpus, provide essential information for a pre-pose of the template. The distance between the neighboring lines provides information about the width of the femur—the scaling parameter for the femur shape. The direction of the lines provides the alignment of the femur template as a first rough initialization.

For optimal placement of the template we use the mean structure of a generated statistical shape model along the femur contour. This information is matched in the local search area starting from the rough initialization along the femur direction using translation and scaling. For every possible pose we calculate the cross-correlation coefficient between the gradient of the template structure and the local area gradient along the posed template shape on the X-ray using 64 positions along the shape. The pose with the highest correlation coefficient reveals the proper parameters for optimal placement of the template.

The segmentation itself is done with an optimized active shape modeling technique. For generating an optimal shape prior we use minimum description length (MDL), based on 200 supervised manual segmented femur shapes. Our segmentation is based on a coarse to fine scaling technique including a profile scale space method.

To answer the question of how close the template should be placed for successful segmentation, we have calculated the distance between the posed template and the manual segmented femur contour based on two characteristic points: femur neck and femur center.

Using the knowledge-based technique we have located 95% of the femur shapes of $N = 117$ X-rays. About 83% of the remaining shapes ($N = 112$) have been found exactly within a range of a point-to-point error of $E_{\text{pt–pt}} \sim 14$ pixels and a point-to-boundary error of $E_{\text{pt–bd}} \sim 9$ pixels. The exact delineation failed in 17%, especially due to low contrast.

It seems that all the initialized templates are in the range for succeeding with a distance of less than 90 pixels. For comparison only, the mean distance between the femur center and neck has been about ~ 190 pixels for all shapes.

With an adequate knowledge-based template initialization and an improved ASM this pipeline may provide a robust tool for delineation of femur shapes in conventional X-ray images.

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