ASM Driven Snakes in Rheumatoid Arthritis Assessment

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Abstract. In this paper a method is proposed that combines active shape models (ASM) and active contours (snakes) in order to identify fine structured contours with high accuracy and stability. Based on an estimate of the contour position by an active shape model the accuracy of the landmarks and the contour in between is enhanced by applying an iterative active contour algorithm to a set of gray value profiles extracted orthogonally to the interpolation obtained by the ASM. The active shape model is trained with a set of training shapes, whereas the snake detects the contour with fewer constraints. This is of particular importance for the assessment of pathological changes of bones like erosive destructions caused by rheumatoid arthritis.

1 Introduction

Rheumatoid arthritis is an incurable disease leading to disability and increased mortality. The accurate determination of its progression is a decisive factor during treatment and clinical studies. In particular the quantification of erosive destructions of bony contours in hand radiographs provides valuable information [10]. An automation is highly desirable by means of objectivity, accuracy and reproducibility of quantification results.

Active shape models (ASM) [2] are a frequently used tool in medical image analysis. They efficiently search images with a flexible and compact model using a priori knowledge derived from training data. It is possible to recognize objects with high variation in shape and appearance. The result provides a parametric description of the identified shape.

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Fig. 1. Metacarpal bone with erosive changes (arrows) and result of an ASM search.

Despite their high speed, generality and robustness against bad initialization [9] ASM segmentation algorithms face certain drawbacks: (1) ASMs are based on distinct and recognizable features that have to be trained. (2) In order to avoid an over-constrained model of shape variation the training set has to be sufficiently large. Since during training the landmarks have to be annotated manually, this is costly and time consuming. (3) Due to the linearity of the model it is not capable of reconstructing severe pathological changes like erosions caused by rheumatoid arthritis. Non-linear shape models have been introduced in [4], though these models are more flexible the first two problems remain. In Fig. 1 a bone in a hand radiograph showing erosive destructions and the result of an ASM search are depicted. The ASM result does not adapt to the erosions.

Active contours (Snakes) [6] on the other hand adapt even to fine structures, require no training but are very sensitive to inaccurate initialization [9]. They adapt to image content by iteratively solving an energy minimizing problem influenced by external and internal forces. By applying non-conservative external force fields the convergence of snakes to *contour concavities* is enhanced. In [11] *gradient vector flow* is utilized to generate a non conservative external force field.

In this paper we introduce an approach that reduces drawbacks of both methods by combining the advantages of ASMs and snakes. *ASM driven snakes* enhance the result of ASMs and provide high accuracy and robustness, while the size of the necessary set of samples for ASM training can be decreased. The method not only enhances the accuracy of landmark detection of a standard ASM but identifies contour lines in between ASM landmarks. The approximation of fine shape details is restricted only by parameters of the inner force field of a snake. This is in contrast to [5]. A priori knowledge is used only with respect to the gray level neighborhood of the landmarks while the tie of the final result to the shape model is gradually decreased. These are crucial properties in detection of pathologic changes like bone erosions, since they cannot be modeled accurately with ASMs.

The paper is organized as follows: In section 2 the algorithm is explained in detail, section 3 presents results of experiments and in section 4 a conclusion and a brief outlook to future research are given.

2 Methods

The utilized methods will be described briefly, followed by a detailed description of the algorithm.

2.1 Active Shape Models

We apply a standard ASM algorithm [3,2] in order to estimate the bone contour.

An active shape model $\mathbf{S}$ represents a shape as a set of labeled points (landmarks) $\mathbf{x} = (x_1, x_2, \dots, x_{n_a})$. Each $x_i = (x_i^1, x_i^2)$ is a point in the spatial domain of the image. The *pose* i.e. effects of scaling, rotation and translation $\mathbf{x} = L(s, \phi)\mathbf{x}' + X_c$ are treated during the alignment procedure. After determining a mean shape $\bar{\mathbf{x}}$ the modes $\mathbf{m}_i$ of variation i.e. the deformations of the shape are found by applying principal component analysis to the deviations of the training samples $d\mathbf{x}_i = \mathbf{x}_i - \bar{\mathbf{x}}$. The matrix $\mathbf{M} = (\mathbf{m}_1, \mathbf{m}_2, \dots, \mathbf{m}_t)$ built by the first t modes can be used to approximate any shape in the training set by building a sum $\mathbf{x} = \bar{\mathbf{x}} + \mathbf{M}\mathbf{b}$ weighted by $\mathbf{b} = (b_1, b_2, \dots, b_t)$.

In order to model the gray level neighborhoods of the landmarks x_i for each model landmark x_i , a one dimensional profile g_{ij} is extracted from the training image j . It has length n_p , is centered at the point x_i and is orthogonal to the curve passing through the landmarks. Information about the gray level neighborhood for each landmark in the model is represented by $g_i = 1/n \sum_{j=1}^n g'_{ij}$ i.e. the mean of the derivatives of $\{g_{ij} | j = 1, \dots, n_t\}$.

During the search for a shape $\mathbf{x}$ in an input image, suggested movements for each approximated model point $\hat{x}_i$ are calculated based on a convolution of the derivative of the actual gray level profile extracted from the image and g_i resulting in a cost function. After the points have been moved orthogonally to the ASM contour pose and shape parameters are adjusted so that $\hat{\mathbf{x}} = (\hat{x}_1, \hat{x}_2, \dots, \hat{x}_{n_a})$ is represented by the model $\mathbf{S}$. This adjustment is not restricted to orthogonal movements. It is based on a range of plausible deformations i.e. plausible values for the mode coefficients in $\mathbf{b}$. The procedure is iterated until it converges. The result is a set of points $\hat{\mathbf{x}} = (x_1, x_2, \dots, x_{n_a})$ being an estimation of the landmark positions in the image.

2.2 Snakes

A snake [6,11] $\mathbf{x}(s) = [x(s), y(s)]$ is a curve that moves through the spatial domain of an image $P(x, y)$ to minimize an energy functional. The functional is controlled by an internal force field formed by weighting parameters α and β representing tension and rigidity of the curve and an external force field. The external force field is based on an edge map $f(x, y) = -E_{ext}(x, y)$ derived from

Fig. 2. (a) Profiles orthogonal to the spline interpolation of the landmarks (represented by larger circles). (b) The resulting set of gray level profiles P . (c) edge map f . (d) detail of vector field $\mathbf{v}$

the image. The snake satisfies the force balance equation $\mathbf{F}_{int} + \mathbf{F}_{ext} = 0$ where $\mathbf{F}_{int} = \alpha \mathbf{x}'' - \beta \mathbf{x}''''$ and $\mathbf{F}_{ext} = -\nabla E_{ext}$. A stable state of the curve is reached iteratively[6].

A gradient vector flow (GVF) field [11] is a non-conservative vector field $\mathbf{v}(x, y) = [u(x, y)v(x, y)]$ that minimizes the energy functional

$$\int \int \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |\mathbf{v} - \nabla f|^2 dx dy. \quad (1)$$

It is nearly equal to the gradient of the edge map $\mathbf{v} \approx \nabla f$ if ∇f is large, and has low variation in homogenous regions of f .

2.3 The ASM Driven Snakes Algorithm

A coarse initialization of the ASM is achieved by an artificial neural network (in particular a local linear mapping net) which detects the fingertips and joints in a radiograph. For details please refer to [7]. The proposed algorithm then proceeds in the following main steps:

1. The shape is represented by landmarks $\mathbf{x} = (x_1, x_2, \dots, x_{n_a})$. An ASM search on the input image $\mathbf{I}$ results in an estimate $\hat{\mathbf{x}}_1^{ASM} = (\hat{x}_1^1, \hat{x}_1^2, \dots, \hat{x}_1^{n_a})$ of the landmark positions. The ASM has been trained on a set of training samples.

Fig. 3. $\square$: manually assigned landmarks. (a) Landmarks detected by an $\triangle$ ASM and by $\circ$ ASM driven snakes; (b) Contour in between landmarks, dashed line: detected by ASM; solid line: detected by ASM driven snakes.

2. The positions of the landmarks $\hat{x}_1^i$ building $\hat{\mathbf{x}}_1^{ASM}$ are interpolated by a cubic spline. This yields a fine approximation of the entire contour parameterized by the square root of chord-length [8] based solely on the landmark positions of the ASM search result. Gray level profiles p_i with length m are extracted from the image. They are orthogonal to the spline interpolation and build a matrix $\mathbf{P} = [p_1, p_2, \dots, p_n]$. Fig.2a shows the original positions of the gray level extraction points in a clipping of $\mathbf{I}$ around a metacarpal bone. Gray values along every line orthogonal to the spline interpolation build one column in $\mathbf{P}$. We view $\mathbf{P}(x, y)$ with $(x, y) \in [0, n] \times [0, m]$ as a continuous distribution of gray values. Fig.2b depicts the gray level matrix $\mathbf{P}$ resulting from Fig.2a. Positions of landmarks $\hat{x}_i$ that have been projected into the new domain are marked by circles. The spline interpolation in between the ASM landmarks is positioned at points $\mathbf{s}_1^{ASM} = (x, y)_{i=1, \dots, n} : (x, y)_i = (i, m/2)$ in $\mathbf{P}(x, y)$. It serves as initialization for an iterative contour search with snakes in $\mathbf{P}$. Successive estimates of the contour will be denoted by $\mathbf{s}_2, \mathbf{s}_3, \dots, \mathbf{s}_i, \dots$ and exhibit increasingly looser bonds to the initialization $\mathbf{s}_1^{ASM}$.

3. An edge map $f(x, y)$ (Fig. 2c) is generated based on the matrix $\mathbf{P}$.

$$f(x, y) := \text{sign}(c(x, y)) * (\tau c(x, y) + \eta(\mathbf{a}_b(x) \star d\mathbf{P}(x, y)/dy) + \gamma o(x, y)) \quad (2)$$

where $*$ denotes pixelwise multiplication. $c(x, y)$ is the accumulation of outputs of a sequence of Canny edge detectors [1] $C(x, y, \sigma, t)$ with pairs of varying hysteresis thresholds $\mathbf{t} = \mathbf{t}_1, \mathbf{t}_2, \dots, \mathbf{t}_c$ applied to $\mathbf{P}(x, y)$. It forms the fundament for the weighted edge map. $\mathbf{a}_b(x)$ are generated by interpolating values of neighboring ASM profiles g_i and g_j with $i \leq x < j$. The convolution $(\mathbf{a}_b(x) \star d\mathbf{P}(x, y)/dy)$ corresponds to the similarity of the derivatives of profiles extracted from the input image and an interpolation of profiles to be found by the ASM. This term

links the snake search to the a priori appearance information in the ASM. The binary function $o(x, y) \in \{0, 1\}$ equals 1 iff the point (x, y) is part of an edge that crosses the preceding estimate of the contour $\mathbf{s}_i$ i. e. during the first iteration this is $\mathbf{s}_1^{ASM}$.

The snake parameters α and β steer the bond between each new estimate $\mathbf{s}_{i+1}$ and $\mathbf{s}_1^{ASM}$. Increasing the parameters α and β cause a higher similarity in direction with the ASM estimate $\mathbf{s}_1^{ASM}$ but prevents fitting of fine structure. The edge map parameter τ controls the influence of an edge detector with gradually lower weighted branchings to the external force field corresponding to the search for a continuous contour of the bone. η steers the effect of the appearance information stored in the ASM. γ controls the effect of the estimate $\mathbf{s}_i$ on $\mathbf{s}_{i+1}$ by determining the force that drags $\mathbf{s}_{i+1}$ to connected edges that cross $\mathbf{s}_i$.

4. By generating a GVF vector field $\mathbf{v}$ (Fig. 2d) from f and applying the standard iterative snake algorithm (Sec. 2.2) a new approximation of the transformed shape and contour positions in between landmarks in $\mathbf{P}$ is derived. The active contour is initialized on the position of $\mathbf{s}_1$ and converges to a new estimation of the contour and the set of landmarks $\mathbf{s}_2$.

5. The resulting points of $\mathbf{s}_i$ are back projected on the image. The result is a new estimate $\hat{\mathbf{x}}_i$ of the landmark positions as well as a contour description in between landmarks that more accurately adapts to the image content.

Steps 3 and 4 can be iterated with varying parameters for the active contour by generating a GVF force field and fitting a new active contour $\mathbf{s}_{i+1}$ based on $\mathbf{s}_i$. By increasing elasticity of succeeding snakes they gradually adapt to finer structures.

3 Experiments

We evaluated the method with respect to (1) improved accuracy of landmarks represented by the ASM and (2) accuracy of the located contour in between landmarks.

Experimental Setup: Tests were performed on hand radiographs with and without erosive changes. The edge length of a pixel is 0.0846mm. The ASMs were initialized randomly with varying initialization error. The performance of *ASM* and *ASM driven snakes* were evaluated with two ASM training sets T_{15} (15 training samples) and T_{30} (30 training samples). Each bone was represented by 42 landmarks. The test set consisted of 10 manually assigned shapes.

Results: The ASM driven snakes decrease position error only orthogonally to the contour. With T_{30} the median orthogonal landmark position error was reduced from originally 3.7 pixels to 1.33(36%) pixels by 3 succeeding snakes with increasing elasticity. In Fig. 3a true landmarks, landmarks found by an ASM and landmark positions improved by ASM driven snakes are depicted. The percentage of landmarks lying within a 3 pixel error corridor around the true shape was increased from 40% to 75%. Fig. 4 shows the a plot of the distribution of landmark position errors (in pixels) orthogonal to the contour. The distribution

Fig. 4. Orthogonal error distribution for landmarks found by ASM and ASM driven snakes.

Fig. 5. Results: dash-dotted line: ASM search; solid line: ASM driven snake with high elasticity; dashed line: low elasticity.

of ASM driven snakes results is considerably more concentrated around the true contour.

The median error of an ASM trained with T_{15} is 3.78 pixels, training with T_{30} decreased the error to 3.71 pixels, ASM driven snakes based on T_{15} achieve a median error of 1.45 pixels. Thus ASM driven snakes allow for reduction of training set size.

Fig. 3b shows the result of an ASM (dashed line) compared to the result with ASM driven snakes (solid line) on the joint region of a bone. The ASM driven snake adapts well to the erosion.

In Fig. 5 the result of an ASM search (dash-dotted line) and two snakes with different elasticity parameters (dashed and solid line) are depicted. Both perform equal on the healthy bone contour but differ at the erosion. Therefore, this method can be used for quantitative assessment of bone erosions. Preliminary experiments using a simple classifier on features derived from the ASM and the snakes show promising results in this respect.

4 Conclusion

A method to identify bone contours in radiographs by applying a combination of active shape models and active contours is presented. The advantages of both

methods i. e. robustness against inaccurate initialization and high accuracy even on contours hard or impossible to model are preserved. The presented algorithm is generalizable to other anatomical structures. The work is of particular interest for the automated quantification of erosive destructions caused by rheumatoid arthritis. Future research will focus on the analysis of the derived contour description. An automated discrimination of pathological changes is work in progress and shows promising results.

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