Human-computer interaction in medial image analysis
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Chapter 6

Applying the Framework for Interactive Segmentation to Delineate the Joint Space in Osteoarthritic Ankles*

“If you have built castles in the air, your work need not be lost; that is where they should be. Now put the foundations under them.”

in Walden, by Henry David Thoreau.

In many medical applications, segmentation of the object of interest remains an obstacle for accurate and reliable digital image analysis. Particularly when image quality is low, generic automatic segmentation techniques often do not provide satisfactory results, therefore a dedicated segmentation solution is needed. In many of these applications, however, the development of such a dedicated method is constrained by time and cost, with the consequence that, in practice, the segmentation of the image is solved with a fully manual procedure. As an alternative solution for such cases, we put forward the framework for interactive segmentation proposed in chapter 3. This framework offers a design and implementation infrastructure that can be used for the development of interactive segmentation solutions with affordable effort.

In this chapter we show how the framework for interactive segmentation has been applied to develop a dedicated solution for a difficult segmentation problem. The goal of the medical application is to assess the severity of osteoarthritis in the ankle joint based on digitised radiographs. Because the visual evidence of the object under study is very faint in these images, assistance of a human operator is required in the

*This work was developed with Anne Karien Marijnissen (Department of Rheumatology & Clinical Immunology) and Koen Vincken (Image Sciences Institute), University Medical Center Utrecht, The Netherlands. A preliminary version of this chapter was presented at the IPMI'99 conference.
segmentation process. We aim at an interactive solution where user intervention is efficient and the segmentation results are objective whenever possible, open for future improvement.

This text is organised as follows: section 6.1 briefly presents the medical application and section 6.2 describes the current semi-automatic segmentation process. Section 6.3 presents the new interactive segmentation method based on a heterogeneous deformable model and specialised interaction tools. Preliminary results obtained with this method are presented and discussed in section 6.4.

6.1 Medical Application

Osteoarthritis is a disease of joints connecting two or more bones characterised by joint stiffening and pain. In this application, the purpose is to assess the severity of osteoarthritis in the ankle joint from radiographic images. The clinical goal is to evaluate the effect of a treatment for this disease, called joint distraction, that is currently applied at the University Medical Center Utrecht - see details in [8].

The structure of interest in this application is the space between the tibia and the talus at the ankle joint - see figure 6.1. The ankle joint space is the region delimited by the boundaries of the tibia and talus at the joint.

![Figure 6.1: The ankle joint space. (a) Coronal dissection of a normal ankle extracted from [7]. (b) Digitised radiograph of a normal ankle, with the medial line of the body at the left. (c) Scheme showing the boundaries of interest (plain lines), the joint space (shaded area), and other boundaries at the joint (dotted lines).](image)

The images used in this application are digitised X-rays of the ankle joint acquired in standardised mortise view (figure 6.1-b): the patient is standing, the foot is turned 20° inwards, and the image acquisition is done with standard settings (50kV, 20mAs, focal film distance of 110 cm). In these images, the medial line of the body is at the left and the lateral side is at the right. The ankle joint space is delineated by two curves corresponding to the boundary of the tibia (upper line) and the talus (lower line) - see figure 6.1-c.

The osteoarthritic ankle is imaged before and after treatment. The other ankle is imaged only once and used as a reference in the study (control ankle). Figure 6.2
6.1. Medical Application

presents examples of images obtained after joint distraction of the osteoarthritic ankle of one patient.

![Figure 6.2: Follow-up of the osteoarthritic ankle of a patient treated with joint distraction. From left to right, images obtained at 12, 24 and 36 months after treatment.](image)

To assess the severity of osteoarthritis in the ankle joint, the following information is quantified on the basis of the boundary of the ankle joint space – see figure 6.3:

- the amount of subchondral sclerosis in the joint, indicated by the average image intensity in the talus and in the tibia near the ankle joint;

- the joint space width, corresponding to the distance between the talus and the tibia at the joint; and

- the joint space angle, indicated by the angle between two lines approximating the boundary of the talus and the tibia.

![Figure 6.3: Parameters to assess the severity of osteoarthritis in the ankle joint.](image)

In this work, we focus on the delineation of the ankle joint space, which is a challenging task for humans and machine alike. First of all, it is difficult to locate precisely the boundary of the ankle joint space due to low image intensity contrast, particularly at the upper boundary. Secondly, the differences among the images over time can be very subtle, so segmentation accuracy is important to obtain measurements that are reliable enough to be used as a criterion for treatment evaluation. Finally, it is important to reduce bias and improve reproducibility in the segmentation process to obtain more objective measurements.
In conclusion, automatic segmentation is unlikely to be achieved in this application due to poor image quality, but manual segmentation is not acceptable due to the need for accurate and reproducible results. A combined solution is therefore needed, such as presented next.

6.2 The Current Semi-Automatic Method for Segmentation and Measurement

The semi-automatic segmentation process currently in use is based on a rigid protocol defining the sequence of operations performed by the user and by the computational method. The protocol constrains user actions when indicating the basic positions used for measurement, aiming at reduced subjectivity in the process. In this case, the parameters used to assess the severity of osteoarthritis at the ankle joint space are estimated on the basis of 10 sets of circles along the edge of the tibia and the talus (see figure 6.4).

![Figure 6.4: Manual sketch of the protocol for semi-automatic segmentation, showing three lines drawn by the user (L₀, L₁, L₂), the segment used as the reference for interaction and measurement (AB) and the image positions used for measurement (circles).](attachment:image.png)

With minimal interaction, the operator draws three reference lines roughly corresponding to the boundary of the talus (lines L₀, L₁ and L₂). The intersections of these lines determine the segment AB, used as a reference for interaction and measurement. Five perpendicular lines to AB are determined and 10 sets of circles are placed along them. The operator adjusts the position of the upper and lower sets of circles along the perpendicular lines, placing them at the correct edge of the tibia and the talus.

The estimation of the joint space width is based on the distance between the
position of the corresponding circles at the boundary of the tibia and talus. The joint space angle is obtained based on the linear regression (least squares method) of the circles positions at the boundary of the tibia and the talus. The amount of subchondral sclerosis is estimated based on the average image intensity inside the circles. These values are normalised with respect to the average intensity inside the reference circle in the tibia, where the bone density is not affected by osteoarthritis. The position of the reference circle is automatically determined at a perpendicular to the line representing the upper boundary - see figure 6.4.

The presentation of a thorough analysis of the results obtained with the current method is outside the scope of this text; refer to [6] for details. Just as an illustration, below we show examples that correspond to fairly enough imaging conditions of a control ankle (figure 6.5) and an osteoarthritic ankle (figure 6.6). The figures show the position of the polygonal lines corresponding to the ankle joint space delineation and the perpendicular lines supporting the circles used to estimate subchondral sclerosis. The results obtained in different segmentation sessions are presented to provide an indication of the variation between observers.

Figure 6.5: Delineation of the ankle joint space in a control ankle obtained by two observers in four segmentation sessions with the semi-automatic method. (a) Grey image. (b) Upper and lower lines. (c) Perpendicular lines.
Figure 6.6: Delineation of the ankle joint space in an osteoarthritic ankle obtained by two observers in four segmentation sessions with the semi-automatic method. (a) Grey image. (b) Upper and lower lines. (c) Perpendicular lines.

The visual inspection of figures 6.5 and 6.6, and the analysis of data not shown here lead to the following conclusions:

- the variation in the polygonal lines delineating the boundary is larger when the ankle joint space is less visible (e.g. figure 6.6-b). This variation affects the reproducibility of the joint width estimation and the calculation of the joint angle;

- the perpendicular lines to the boundary are reasonably stable, leading to reproducible estimation of the amount of sunchondral sclerosis. However, their orientation is given by the boundary of the talus, thus they may be incorrect for the tibia when the joint angle is large (e.g figure 6.6-c).

In conclusion, the current method leaves room for improvement in two ways. Firstly, a more precise representation for the ankle joint space boundary could increase the accuracy and robustness of the estimated parameters. Secondly, the degree of automation of the computational method could be elevated by taking the image data into account whenever possible, leading to more reproducible results and increased operation efficiency.
6.3 The New Interactive Segmentation Method based on FIS

The interactive segmentation method described here has two major goals. The first is to improve the accuracy of the ankle joint space delineation, maintaining the same measurement strategy used in the current semi-automatic method. Specifically, the polygonal curves approximating the upper and lower boundaries with only five points are replaced by continuous curves. Secondly, prior knowledge about the ankle joint space was incorporated to a model-based segmentation method, with the goal of increasing interaction efficiency and delineation reproducibility as much as possible.

The interactive method for the ankle joint space follows the framework suggested in chapter 3, and it was implemented as a customisation of the method described in chapter 5. For completeness of this chapter, a summary is presented below:

- The backbone is a computational method based on prior knowledge about how the ankle joint space boundary is ideally depicted in the radiographic images. The computational method is described in section 6.3.1, and the model used for the boundary is presented in section 6.3.2.

- The results generated by the computational method can be wrong, i.e. different from those expected by the user, when the object in the image deviates too much from the model incorporated in the method. The list of situations for failure of the computational method is discussed in section 6.3.3, with the appropriate model corrections to obtain the desired result.

- The user evaluates the situation at hand based on the visual feedback displayed on the screen. In case of failure, the user provides information that is used to correct the model accordingly, using specialised interactive tools. The user interface is described in section 6.3.4.

6.3.1 Piecewise Deformable Model

The computational method supporting the interactive process is the Piecewise DM method described in detail in chapter 4. Briefly, the novelty of this method consists in allowing for heterogeneous and locally controllable boundary models, that is, each part of the boundary can be characterised in terms of different image and shape feature values.

The objective function minimised by the method is defined as a sum of terms with localised influence, called pieces:

\[
\Theta[C] = \int_t \sum_{j=1}^K W_j(t) \theta[C, M_j](t) \, dt
\]

where \( C \) is the boundary, represented by a cubic B-Spline curve [2], \( t \) is the path parameter to navigate along the curve, \( K \) is the number of pieces, and \( W_j(.) \) is the
weight of piece \( j \). The local deviation function \( \theta(.) \) measures the difference between \( C \) and the model for the boundary piece \( M_j \) as follows:

\[
\theta[C, M_j](t) = \begin{cases} 
  w_{\varphi}(t)\Delta_{\varphi}(t) + w_D(t)D[\sigma(t)](x(t), y(t)) & : t \in [t_1, t_2], \\
  0 & : \text{otherwise},
\end{cases}
\]

where \( \Delta_{\varphi}(.) \) and \( D(.) \) correspond to the difference with respect to the local shape and image features, \( w_{\varphi} \) and \( w_D \) are the corresponding weights of the local features, and \([t_1, t_2]\) is the curve segment where the piece is defined. The deviation measured by \( \Delta_{\varphi}(.) \) and \( D(.) \) is normalised to variations within a given tolerance, determined from the ensemble of admissible results.

Apart from allowing the definition of a heterogeneous model, the Piecewise DM is flexible to easily accommodate for local corrections resulting from interaction by adding or reconfiguring the model for boundary pieces.

### 6.3.2 A Boundary Model for the Ankle Joint Space

The boundary model describes the local image and shape properties of the ankle joint space as ideally depicted in radiographic images acquired in standardised mortise view (see figure 6.7). This model is based on a study of anatomy, a set of images, and the corresponding segmentation results obtained with the semi-automatic method.

![Figure 6.7: A heterogeneous model for the ankle joint space boundary. Shape: each curve is composed of three straight segments linked by two corners. Visual evidence: bright line for the upper curve and dark-to-bright edge for the lower curve.](image)

The boundary model is implemented with two independent piecewise deformable models. Only the central stretch is relevant for measurement, while the other pieces provide an anchor for segmentation and adequate continuity conditions at the endpoints. In an ideal situation, the central stretch is a smooth curve roughly horizontal with respect to the image grid. The upper curve is located at a ridge in the image intensity landscape, and the upper curve is located at a discontinuity of the image intensity function. More simplified boundary models are adopted for the other parts, leaving room for improvement. The types of local image and shape features adopted to characterise the boundary are described below.
Local Shape Features

Local shape is characterised by the change of the curve's turning angle [4]:

\[ \varphi'(t) = \frac{x'(t)y''(t) - x''(t)y'(t)}{x'(t)^2 + y'(t)^2}, \]

where \( x'(t) \) and \( x''(t) \) are the first and second order derivatives of \( x(t) \), and likewise for \( y \). This curvature-based feature is invariant to the size, position and orientation of the contour in the image. Figure 6.8 illustrates the values corresponding to the upper and lower boundaries of an arbitrary ankle joint space.

![Figure 6.8: Local shape properties of the ankle joint space boundary. (a) Examples of curves representing the upper and lower boundaries. (b) Value of \( \varphi'(t) \) for these curves.](image)

The measure of deviation with respect to local shape \( \Delta \varphi'(\cdot) \) follows the Mahalanobis distance [1]:

\[ \Delta \varphi'(t) = \left( \frac{\varphi'(t) - \hat{\varphi}'(t)}{\tau(t)} \right)^2, \]

where \( \hat{\varphi}'(t) \) is the expected feature value and \( \tau(t) \) is the variation tolerance. Both values are determined based on prior knowledge about local variations and are adapted based on information derived from interaction.

Local Image Features

Local image features \( D[\sigma](x(t), y(t)) \) capture the visual evidence of an object, i.e., information derived from the image data that indicate the presence of object boundaries. In this application, two basic types of visual evidence characterise the boundary of interest: bright lines (upper) and bright-to-dark edges (lower) - see figure 6.9.
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Figure 6.9: Local image properties of the ankle joint space boundary: the lower part is located at a large discontinuity of image intensity, and the upper part is located at a ridge. (a) Image intensity landscape. (b) Image intensity profile at selected perpendiculars to the boundary.

The detectors of visual evidence available in this implementation are based on scale-space theory [5], corresponding to filters $\Phi[\sigma]$ that operate on the grey image $I(x, y)$ to determine the presence of lines and edges at scale $\sigma$. The dynamic range of $D(.)$ is normalised into $[0, 1]$, with zero corresponding to maximal response. The types of detectors adopted in this application are defined in Table 6.1 and illustrated in Figure 6.10.

<table>
<thead>
<tr>
<th>Detector $D$</th>
<th>Visual Evidence</th>
<th>Image Structure</th>
<th>Filter $\Phi[\sigma]$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_{\nabla I}$</td>
<td>Step-edge</td>
<td>Gradient</td>
<td>$\sigma \sqrt{I_x^2 + I_y^2}$</td>
</tr>
<tr>
<td>$D_{\nabla_y I}$</td>
<td>Horizontal edge</td>
<td>Magnitude</td>
<td>$\sigma</td>
</tr>
<tr>
<td>$D_{\nabla^2 I}$</td>
<td>Bright line</td>
<td>Laplacian</td>
<td>$\sigma^2</td>
</tr>
<tr>
<td>$D_{\kappa I}$</td>
<td>Horizontal bright line</td>
<td>Curvature</td>
<td>$-\sigma \frac{I_{yy}}{\sqrt{I_x^2 + I_y^2}}$</td>
</tr>
</tbody>
</table>

Table 6.1: Types of detectors of local image structure based on [3], with responses normalised to the scale [5]. $I_x$ and $I_{xx}$ denote the partial image derivatives $\frac{\partial}{\partial x} I$ and $\frac{\partial^2}{\partial x^2} I$, and $\sigma$ is the size of the kernel used to compute Gaussian derivatives.

To obtain responses that are less sensitive to the choice of scale, the detector is applied at three different scales and the strongest outcome at each grid position is selected. This strategy implements a simple multi-scale mechanism that provides a balance among the scale corresponding to the size of the ankle joint space in the image, a smaller scale for improved edge location, and a larger scale for robustness.
Figure 6.10: Detectors of visual evidence. Regions with maximal detector response are displayed in black and low response areas are shown in white.

**Summary**

A summary of the complete boundary model for the ankle joint space is shown in tab.6.2.

<table>
<thead>
<tr>
<th>Boundary Piece</th>
<th>Upper Boundary</th>
<th>Lower Boundary</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$D$</td>
<td>$w_D$</td>
</tr>
<tr>
<td>Lateral stretch</td>
<td>$D_{\gamma 1}$</td>
<td>0.8</td>
</tr>
<tr>
<td>Lateral corner</td>
<td>$D_{\gamma 2}$</td>
<td>0.9</td>
</tr>
<tr>
<td>Central stretch</td>
<td>$D_{\kappa y}$</td>
<td>0.7</td>
</tr>
<tr>
<td>Medial corner</td>
<td>$D_{\gamma y}$</td>
<td>0.9</td>
</tr>
<tr>
<td>Medial stretch</td>
<td>$D_{\gamma 2}$</td>
<td>0.8</td>
</tr>
</tbody>
</table>

Table 6.2: Configuration of each piece in the boundary model for the ankle joint space, showing the type of image feature $D$, its weight $w_D$, and the expected value $\varphi'$ and tolerance $\tau$ for the shape feature, with $w_{\varphi'} = 1 - w_D$.

This boundary model takes into account prior knowledge about how the ankle joint space is ideally depicted in the radiographic images, being heterogeneous in nature. It is valid for most images, but the implementation admits modification in selected boundary segments as a consequence of interaction.

### 6.3.3 Cases of Failure

The result obtained with the computational method can be wrong when the contour in the image locally deviates from the ideal situation described by the segmentation model in tab.6.2. A limited number of situations for failure of the automatic method were identified as a result of the systematic analysis proposed in chapter 3. Since only the delineation of the central stretch is used for measurement, we limit the discussion to cases of failure that can occur in this part of the boundary only.

The same procedure described in chapter 5 is adopted here to correct the boundary model. For completeness, below we present the cases for failure that occur in this
application, repeating the correction procedure applied to the curve interval affected by interaction given by \([t_1, t_2]\).

**Case #1: Low Visual Evidence**

This situation occurs when the contrast at the ankle joint space boundary is too low (see figure 6.11).

![Figure 6.11: Example of low visual evidence at the central stretch of the ankle joint space.](a) Grey image. (b) Response of \(D_{xy}\), with no significant valley corresponding to the upper boundary.

Two corrections are necessary:

1. Locally reduce the relative importance of the image component in the model:

\[
\begin{align*}
w^*_D(t) &= \begin{cases} 
  z_w \cdot w_D(t) & : t \in [t_1, t_2] \\
  w_D(t) & : \text{otherwise,}
\end{cases}
\end{align*}
\]

where \(w^*_D\) is the locally modified weight for the image feature and \(z_w\) is the reduction factor, with \(0 < z_w < 1\).

2. Attract the contour \(C\) to the current curve \(C_u\) by adding a local constraint measuring the Euclidean distance between corresponding points in these curves:

\[
\begin{align*}
\theta^*(t) &= \begin{cases} 
  \theta(t) + w_E(t)\Delta_E[C, C_u](t) & : t \in [t_1, t_2], \\
  \theta(t) & : \text{otherwise,}
\end{cases}
\end{align*}
\]

with

\[
\Delta_E[C, C_u](t) = \left( \frac{C(t) - C_u(t)}{d} \right)^2, \quad t \in [t_1, t_2],
\]

where \(d\) is the tolerated distance from the given curve. The weight of the new constraint is determined as follows:

\[
w_E(t) = 1 - w^*_D(t) - w^*_w(t).
\]
Case #2: Wrong Visual Evidence

This case may occur when the upper and lower lines are too near or when there are misleading boundaries due to the projection of 3-D anatomical structures in the radiograph. The image in figure 6.12 is an example where the curve may be attracted by the wrong boundary.

Figure 6.12: Example of a situation where the result may be incorrect due to disturbing boundaries at the central stretch of the ankle joint space. (a) Grey image. (b) Response of $D_{xy}$ showing a possibly misleading valley near the upper boundary due to the effect of projection in the radiograph.

Three corrections are necessary in this case:

1. Locally reduce the scale used to detect image features:

   $\sigma^*(t) = \begin{cases} 
   z_{\sigma} \cdot \sigma(t) & : t \in [t_1, t_2] \\
   \sigma(t) & : \text{otherwise},
   \end{cases}$

   where $\sigma^*$ is the locally modified scale and $z_{\sigma}$ is the reduction factor, with $0 < z_{\sigma} < 1$.

2. Locally reduce the relative importance of the image component in the model - see case #1.

3. Attract the contour to the curve $C_u$ indicated by the user - see case #1.
Case #3.A: Unseen Visual Evidence

This case happens when the image intensity profile at ankle joint space boundary is different from expected, such as a bright line instead of a bright-to-dark edge and vice-versa – see figure 6.13.

Figure 6.13: Illustration for the case of unseen visual evidence at the lower boundary of the ankle joint space. (a) Grey image. (b) The detector $D_{v_x}$ does not respond well locally. (c) Another detector, $D_{k_y}$, responds more strongly.

The adequate correction in this situation is to locally replace the type of image feature $D$:

$$D^*(t) = \begin{cases} D_u(t) & : t \in [t_1, t_2] \\ D(t) & : \text{otherwise,} \end{cases}$$

where $D^*$ is the locally modified image feature term and $D_u$ is the type of image feature indicated by the user.

Cases #3.B and #3.C: Distortion from Local and Global Geometry

The case of distortion from local geometry may occur when the central stretch is less smooth than expected. Since the images do not provide enough visual detail about the ankle joint space, it is unlikely that this case will occur in practice. The case of distortion of global geometry does not apply here because no global shape model is used for the central part of the boundary.

In conclusion, there is no need to implement corrections to cases #3.B and #3.C because they do not occur in practice in this application.
6.3.4 User Interface

Interaction is used to prevent, to detect and to recover from a failure of the automatic method. Prevention from failure is obtained in two ways: (1) via an interactive initialisation procedure, where the user provides information that is used for basic configuration of the Piecewise DM, and (2) by asking the user to confirm or correct the current segmentation model before running the Piecewise DM optimisation. Detection of failure is obtained by asking the user to confirm the contour obtained with the automatic method, and recovery is achieved by allowing the user to correct the curve if it does not correspond to the desired segmentation result. In all cases, user intervention is done with specialised interactive tools and supported by visual feedback about the current state of the segmentation process.

To initiate the process, the user draws a rectangle containing the ankle joint space, the region of interest (ROI) - see figure 6.14-a. The width of the ROI is used to roughly estimate the size of the ankle joint space in pixels and to determine the adequate scale to compute image features.

The segmentation of a boundary starts with the user adjusting a template to the image - see figure 6.14-b. The adjusted template is used to construct the initial curve for the Piecewise DM (see figure 6.14-c), with the corners serving as references to define the pieces in the boundary model in tab.6.2.

![Figure 6.14: Steps in the interactive initialisation of the segmentation process. (a) The Region of interest (ROI). (b) The template. (c) The initial curve constructed based on the template adjusted to the lower boundary.](image)

Once initialised, the deformable model is displayed using a simple and intuitive abstraction: the current contour is represented by an open curve on the grey image, and the deformation forces are visualised as arrows. Intuitively, these arrows indicate the preferred direction of local deformation to obtain a contour where the deviation from the ideal model is minimal: the smaller the arrows, the better the local agreement between the contour on the image and the model. The deformation forces are computed based on the gradient of $\Theta$, as described in chapter 4.

This visual feedback indicates:

- The result is correct when the curve is located at the desired image position;
- The model is correct when the arrows point to the desired image position (e.g.}
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figure 6.15-a), indicating that deformation will lead to the desired segmentation result; and

- The model is wrong when the arrows do not point in the direction of the desired result (e.g. figure 6.15-b), corresponding to one of the cases of failure described in section 6.3.3.

![Figure 6.15: Visual feedback about the current state of the segmentation process, showing the current contour and the local deformation forces. (a) The contour is incorrect, but the model is correct, since the deformation forces point to the right direction. (b) Forces point into the wrong direction due to wrong visual evidence (case #2).](image)

As an additional support to the identification of the case of unseen visual evidence, a menu of possible image feature detectors ($F_{V_y}$ and $F_{k_y}$) is also displayed to the user, such as illustrated in figure 6.10.

The analysis of the visual information on the screen enables the user to evaluate the situation at hand and choose the appropriate interactive tool from the list below:

- **Edit curve**: if the contour position is wrong, the user directly manipulates the curve with the mouse. The initial curve used for deformation is replaced by the contour edited by the user.

- **Confirm model**: if the forces point to the right direction, the user confirms the model, activating the deformation process.

- **Correct model**: if the forces point to the wrong direction, a model correction is needed. The user chooses the tool corresponding to the case of failure at hand (low, wrong, or unseen visual evidence), and indicates the contour segment where it applies with two points in the image. For the case of unseen visual evidence, the user also chooses another type of detector from the menu. The model is corrected as described in section 6.3.3.
• Confirm curve: if the contour position is correct and the forces are small, the user indicates that the desired segmentation result has been obtained, and the process ends.

The screen is always updated after user intervention. Table 6.3 presents a summary of the situations indicated by the visual feedback on the screen, the user intervention needed in each case, and the corresponding interpretation by the program. Note that we assume that the user is capable of identifying the case at hand based on the visual information displayed on the screen.

<table>
<thead>
<tr>
<th>Visual State</th>
<th>User Action</th>
<th>Program Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contour</td>
<td>Forces</td>
<td></td>
</tr>
<tr>
<td>Wrong</td>
<td>Wrong</td>
<td>Edit curve</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>Confirm model</td>
</tr>
<tr>
<td>Right</td>
<td>Wrong</td>
<td>Tool: Low visual evidence</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Point a curve interval</td>
</tr>
<tr>
<td>Right</td>
<td>Wrong</td>
<td>Tool: Wrong visual evidence</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Point a curve interval</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tool: Unseen visual evidence</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Point a curve interval</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Choose an image feature</td>
</tr>
<tr>
<td>Invisible</td>
<td>Confirm result</td>
<td>End</td>
</tr>
</tbody>
</table>

Table 6.3: Summary of the situations for user intervention determined from the visual information displayed on the screen, the corresponding action by the user and the interpretation by the program. The correction for each case of failure is described in section 6.3.3.

In conclusion, this interaction scheme provides an integrated solution of a computational method combined with user steering where operation is efficient, simple, and intuitive.

6.4 Preliminary Evaluation

Two experiments were performed as a preliminary evaluation of results obtained with an implementation of the new interactive method based on FIS. Below we discuss these results in terms of reproducibility, faithfulness, usability and usage for the quantification of the severity of osteoarthritis.

6.4.1 Reproducibility and Faithfulness

The goal of this experiment was to obtain an initial assessment of *reproducibility* (the same delineation is obtained in different segmentation sessions with the same intention) and *faithfulness* (the delineation corresponds to the correct boundary). For this purpose, a set of 10 selected images were segmented by a non-medical user
(e.g. figure 6.16). In this experiment, the user did not have to correct the boundary model.

Figure 6.16: Results obtained interactively by a non-medical user in 3 segmentation sessions (mostly identical in the central part). (a) Control ankle. (b) Osteoarthritic ankle.

Reproducibility was assessed as follows: each image was segmented 3 times by the same user, with intervals of one day and one week between sessions. Figure 6.17 presents the variation among the results obtained in the 3 sessions. The variation corresponds to the mean distance in millimetres from all points in one curve to all the other curves, taking into account only the central part of the contour.

Figure 6.17: Variation in the results obtained interactively by one user in 3 segmentation sessions: mean (bars), standard deviation and maximum (error bars) per image, and mean for all images (dotted line).

Considering all images, the mean variation is .11mm, with $\mu = .16 \pm .15$mm for the upper boundary and $\mu = .06 \pm .03$mm for the lower boundary. Note that the variation for the upper boundary is larger for all images. Figure 6.16 shows examples where the intra-operator variation is small. The largest variation was observed for an
image with very low contrast, where the boundary is hardly visible. Note that the results obtained with the semi-automatic method for this image also present large variation (figure 6.18).

Figure 6.18: Largest intra-operator variation. (a) Results obtained with the new interactive method: $\mu = .55 \pm .41$mm (upper) and $\mu = .13 \pm .18$mm (lower). (b) Results obtained with the current semi-automatic in 4 segmentation sessions.

Objective assessment of faithfulness is difficult in this application because the truth is not known. The boundaries in figure 6.16 are in agreement with several medical observers, indicating that, in these cases, the outline represents the correct boundary; for other data, however, such a “truth” does not exist due to the lack of agreement among trained users.

Figure 6.19: Distance between the interactive results and the “truth:” mean per image (bars), standard deviation (error bars), and mean for all images (dotted line).

For an initial evaluation of faithfulness, the delineation generated by two medical users using the semi-automatic method was adopted as the ground truth. The points clicked by the user with the semi-automatic method in 4 segmentation sessions are
used to indicate the position of the boundary at the tibia and the talus. The mean distance between these points and the curves obtained interactively with the new method is shown in figure 6.19.

In average, the difference from the “truth” is .47mm, with $\mu = .69 \pm .42$mm for the upper boundary and $\mu = .24 \pm .12$mm for the lower boundary. The results with the best and the worst agreement with the truth are presented in figure 6.20. Larger differences are observed in the upper boundary, where the delineation generated by the semi-automatic method is below the line determined interactively in many images.

![Figure 6.20](image)

**Figure 6.20:** Results with the best and worse agreement with the “truth.” The crosses correspond to positions clicked by the medical users with the semi-automatic method. (a) Best agreement, with difference $\mu = .35 \pm .22$mm (upper) and $\mu = .26 \pm .14$mm (lower). (b) Worst agreement, with difference $\mu = 1.65 \pm .66$mm (upper) and $\mu = .56 \pm .42$mm (lower).

### 6.4.2 Usability and Quantification

The main goals of this experiment were to evaluate the **usability** of the interactive method (the user is able to obtain the desired delineation) and the **quantification** of parameters to estimate the severity of osteoarthritis based on the obtained results. For this purpose, one medical user supervised the segmentation of six images of a patient chosen randomly. Figure 6.21 shows the results obtained for some images.

The new interactive method proved to be usable, since in all cases the medical user was able to obtain the desired delineation, even when corrections to the model were necessary. The delineation of the lower boundary was straightforward in all images. Interaction was necessary only to adjust the template to the image, followed by the deformation of the initial boundary generated automatically by the program. While no corrections to the model were necessary for the lower boundary, the model was wrong for the upper boundary in most images due to unseen visual evidence (case #3.A). The user detected this situation from large arrows pointing in the wrong direction along the initial curve. Segmentation of the upper boundary therefore required
6.4. Preliminary Evaluation

Figure 6.21: Examples of results obtained by a medical user with the interactive method. (a) Control ankle. (b) Osteoarthritic ankle at 0 months. (c) Osteoarthritic ankle at 48 months.

extra interaction to correct the model, by choosing a new image feature detector from an iconic menu with the response of all detectors as shown in figure 6.10.

From the parameters used to assess the severity of OA at the ankle joint, we selected the ankle joint width, which is expected to benefit from increased accuracy in the boundary representation. The ankle joint space width is estimated based on the Euclidean distance between the corresponding points in each boundary, as illustrated in figure 6.22-a. The mean width measured in this fashion is compatible with the estimation done with the semi-automatic method, as shown in figure 6.22-b. Note, however, that the procedure used to align the curves in this study is not optimal, since it does not guarantee that the distance between the corresponding points represents the shortest distance between the two curves, leaving room for improvement.

Figure 6.22: Estimation of the joint space width based on the delineation generated interactively. (a) Boundaries and corresponding points used to compute the distance between the two curves. (b) Comparison of mean width (bars) for different images of one patient using the interactive and the semi-automatic methods.
Apart from providing estimation compatible with previous studies, a precise boundary representation potentially can reveal more information about the joint space geometry than the mean width alone. The integration of all distances along the boundaries gives an indication of the joint area. Moreover, the distance between all points in each boundary can be presented as a width curve illustrated in figure 6.23. The interpretation of the width curve opens up the possibility of a more detailed analysis of the ankle joint space, especially when the boundaries are not parallel.

![Width Curve](image)

Figure 6.23: Width curves, linear regression and the mean width. (a) Control ankle. (b) Osteoarthritic ankle at zero months. See also figure 6.21.

### 6.5 Conclusion

A successful solution for a difficult segmentation problem was presented here, namely the delineation of the ankle joint space boundary of osteoarthritic ankles in radiographs. This application requires interaction because the visual evidence of the boundary of interest is very faint. Since this boundary is the basis to assess the severity of osteoarthritis at the joint, precision and reproducibility are required in addition to the usual demand for efficiency.

In the current semi-automatic procedure, no image data is taken into account by the computational method, and much user participation is needed to indicate the position of a coarse approximation of the boundary in the image. With the new interactive segmentation method, a more precise delineation is obtained with a similar or smaller interaction effort. This was possible because the automation level of the method was elevated by the adoption of a model-based approach.

The initial evaluation presented here indicates that the new method potentially provides reproducible and reasonable delineation of the ankle joint space boundary. Furthermore, the desired delineation always can be obtained using the new method, even when the prior knowledge in the computational method is wrong. This guarantees reliable results, in the sense that they are in agreement with the judgement of
the user. The drawback is that the final outcome of segmentation remains subjective, especially when the visual evidence of the boundary is degraded. And finally, the severity of osteoarthritis in the ankle joint can be quantified on the basis of the delineation obtained with the new interactive method.

A question remains about how the new method will be accepted by medical users from a broader community than considered here. Firstly, the clinical benefit of using a more precise delineation for the quantification of parameters in this application still has to be investigated. And secondly, if this benefit will compensate for the extra effort to learn and operate a more complex method than simply drawing on the image, as currently done.

The new method was developed using the structured approach for interactive segmentation proposed in chapter 3, as a fairly simple customisation of the method described in chapter 5. This strategy proved to be essential for the fast design and implementation of a complete interactive solution that provides good results for a difficult segmentation problem. We believe that other applications, in which the segmentation task is too complicated to rely completely on an automatic method, could be approached in a similar way, instead of adopting a fully manual or a dedicated solution as often done in practice.

Bibliography


