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Performance of local optimization in single-plane fluoroscopic analysis for total knee arthroplasty

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ABSTRACT

Fluoroscopy-derived joint kinematics plays an important role in the evaluation of knee prostheses. Fluoroscopic analysis requires estimation of the 3D prosthesis pose from its 2D silhouette in the fluoroscopic image, by optimizing a dissimilarity measure. Currently, extensive user-interaction is needed, which makes analysis labor-intensive and operator-dependent.

The aim of this study was to review five optimization methods for 3D pose estimation and to assess their performance in finding the correct solution. Two derivative-free optimizers (DHSAnn and IIPM) and three gradient-based optimizers (LevMar, DoNLP2 and IpOpt) were evaluated. For the latter three optimizers two different implementations were evaluated: one with a numerically approximated gradient and one with an analytically derived gradient for computational efficiency.

On phantom data, all methods were able to find the 3D pose within 1 mm and 1° in more than 85% of cases. IpOpt had the highest success-rate: 97%. On clinical data, the success rates were higher than 85% for the in-plane positions, but not for the rotations. IpOpt was the most expensive method and the application of an analytically derived gradients accelerated the gradient-based methods by a factor 3–4 without any differences in success rate.

In conclusion, 85% of the frames can be analyzed automatically in clinical data and only 15% of the frames require manual supervision. The optimal success-rate on phantom data (97% with IpOpt) on phantom data indicates that even less supervision may become feasible.

1. Introduction

Single plane fluoroscopy is commonly used to assess the kinematics of knee prostheses and evaluate their design and in-vivo behavior. To capture the three dimensional (3D) motion of a prosthesis, its position and orientation (pose) are estimated from its silhouette in the individual fluoroscopic frames.

Several methods have been published for estimating the implant pose with reported accuracy of 0.09–0.40 mm for the in-plane position and of 0.35–1.3° for the rotation (Banks and Hodge, 1996; Hoff et al., 1996; Mahfouz et al., 2003; Komistek et al., 2003; Kanisawa et al., 2003; Zuffi et al., 1999; Li et al., 2008; Hermans et al., 2008; Prins et al., 2010). Although the accuracy is considered sufficient, it is our experience that the analysis is operator-dependent and time-consuming.

Most of the time is spent on the supervised pose estimation where the operator needs to review the results for each frame and restart the estimation process in case of suboptimal solutions. The analysis of hundreds of frames of a single patient can take several hours or days, limiting the reproducibility and applicability of fluoroscopy in larger scale studies.

3D pose estimation from 2D image data can be done based on features, intensities or gradients (Markelj et al., 2012). Feature-based methods use features extracted from the image as input for the optimization, such as the outer contour of the implant's silhouette. Intensity-based or gradient-based methods perform the estimation directly on the image or gradient data.

In fluoroscopic analysis, a feature-based approach is commonly applied, as the implant features are easily detected in the image. There are two methods of feature-based pose estimation: forward projection and backward projection. In the first method, a projection of a 3D model is made and correspondences between silhouette and projected model points are determined in the image plane. Subsequently, the dissimilarity between silhouette and projection is minimized. The back-projection method determines

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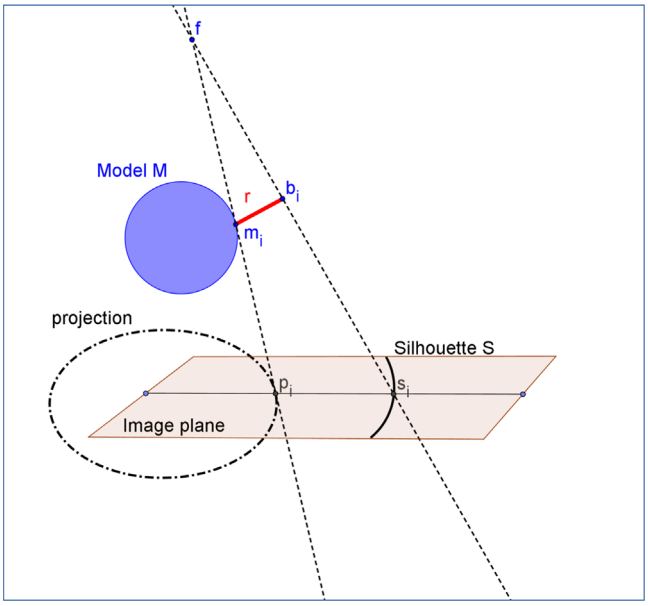

Fig. 1. Distance measure and projection strategy for pose estimation: (1) Each model-point m_i is projected onto the image plane. (2) The correspondence between projected model-points p_i and silhouette-points s_i is determined in the image-plane. (3) Each silhouette point is back-projected to the focus f and the point b_i on the projection line and closest to the corresponding model-point m_i is determined. (4) The residual vectors r_i between each projection line and the 3D model points m_i in its candidate pose define the dissimilarity measure.

the correspondences in the image plane too, but then creates projection lines from the silhouette back to the focus and minimizes the dissimilarity between back-projection lines and the 3D model (see Fig. 1).

In this study, we applied the back-projection strategy, because it computes its dissimilarity in 3D instead of the 2D image plane and consequently takes more depth information into account [Wunsch & Hirzinger]. We defined a nonlinear least squares dissimilarity measure between the back-projection lines and the 3D model. This dissimilarity is then minimized to find the optimal pose of the implant model with respect to the detected silhouette. The classical approach applies Levenberg-Marquardt (Lavallée and Szeliski, 1995; Zuffi et al., 1999; Marquardt, 1963; Levenberg, 1944), but alternative methods have also been proposed (Fregly et al., 2005; Mahfouz et al., 2003).

The accuracy of single-plane fluoroscopic analysis has been assessed only after manual corrections were made. There has been an effect reported of the calibration accuracy on the accuracy of pose estimation (Kaptein et al., 2011). However, there are no studies indicating the autonomous performance of fluoroscopic analysis, e.g. likelihood of success, convergence rates or computational efficiency.

Therefore the aim of this study was to compare the performance of several optimization methods. We examined derivative-free methods, Downhill Simplex Simulated Annealing (DHSAnn) and Iterative Inverse Perspective Matching (IIPM), and gradient-based optimization methods, Do NonLinear Programming 2 (DoNLP2), Interior Point Optimization (IpOpt) and Levenberg-Marquardt. For the latter three optimizers two implementations were evaluated: one with a numerically approximated gradient and one with an analytically derived gradient for computational efficiency. The success-rate, dependency on initial pose and the computation time of each method was investigated in an experiment on phantom and clinical data.

2. Methods

To match an implant model to its silhouette in a fluoroscopic image, an accurate 3D surface model and the outer contour of the silhouette is used (Kaptein et al., 2003). The projection parameters such as focus position and image resolution were determined with Model-based RSA software (Model-Based RSA 3.21, Medis Specials, Leiden, the Netherlands (Kaptein et al., 2003)). The silhouettes were extracted using a Canny edge detector, and the relevant parts on the outer contour were selected manually.

A 3D surface model is defined by a collection of model points, M and the 2D silhouette by a collection of points S. The estimation of the implant pose ρ' minimizes a dissimilarity measure $\delta(\rho, M, S)$, which indicates how "close" the model M fits the detected silhouette S.

$$\rho' = argmin_\rho(\delta(\rho, M, S)) \tag{1}$$

A nonlinear least squares dissimilarity measure $\delta(\rho, M, S)$ was defined between model points m_i and their corresponding silhouette points s_i. A generic optimization method can be applied to minimize the dissimilarity measure. The dissimilarity measure and the optimization method are presented in the following two sections.

2.1. Dissimilarity measure

The pose of a 3D implant model is described by six parameters $\rho = (x, y, z, \alpha, \beta, \gamma)$ which defines a rigid body transformation from a base pose. E.g. applied to each vertex m_i of the 3D model,

$$\phi(\rho, m_i) = R_z(\gamma).R_x(\alpha).R_y(\beta).m_i + (xyz)^T \tag{2}$$

where R_x, R_y, R_z are the rotation matrices around the x, y, z axes with the rotation in YXZ-order and $(xyz)^T$ is the translation vector.

The dissimilarity measure $\delta(\rho, M, S)$ from Eq. (1) is determined in four steps (see Fig. 1):

1. Project the implant model in its pose onto the image plane from the focus f as a projected contour P.
2. Determine the correspondences in 2D by finding point pairs (p_i, s_i): the closest point p_i on the projected contour for each detected silhouette point s_i.
3. Define a 3D back-projection line $b(\lambda)$, parameterized by λ, from each silhouette point s_i to the focus f

$$b(\lambda) = f + \lambda.(s_i - f) \tag{3}$$

and determine the point b_i on this line closest to the model point m_i, where m_i was the point which resulted in p_i after projection in step 1.

The point b_i on this projection line closest to the model is defined by the requirement:

$$(\phi(\rho, m_i) - b_i(\lambda))^T.(s_i - f) = 0 \tag{4}$$

In other words, the vector r_i between b_i and m_i should be perpendicular to the projection line l from f to s_i and λ is calculated as

$$\lambda = \frac{(\phi(\rho, m_i) - f)^T.(s_i - f)}{(s_i - f).(s_i - f)} \tag{5}$$

4. Define a dissimilarity measure between the projection lines and the corresponding model points as the sum of squared lengths of residual vectors r_i.

$$\delta(\rho) = \sum_{\forall i} |r_i|^2 \tag{6}$$

The residual vector r_i is computed for each silhouette-point s_i as the shortest vector between the transformed model-point $m_i = \phi(\rho, m_i)$ and the point b_i on the back-projection line l from s_i back towards the focus f:

$$r_i = \phi(\rho, m_i) - b_i \tag{7}$$

2.1.1. Gradient

If the derivation of an analytical gradient is feasible, this is often more efficient for gradient-based optimizers. For the aforementioned dissimilarity measure, the gradient is calculated as:

$$\nabla_\rho \delta = 2 \sum_{\forall i} J_\phi.(\phi(\rho, m_i) - b_i) \tag{8}$$

Where J is the Jacobian of the rigid body transformation:

$$J_\phi = \left(\frac{\partial\phi}{\partial x} \frac{\partial\phi}{\partial y} \frac{\partial\phi}{\partial z} \frac{\partial\phi}{\partial \alpha} \frac{\partial\phi}{\partial \beta} \frac{\partial\phi}{\partial \gamma} \right) \tag{9}$$