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Kalman smoothing improves the estimation of joint kinematics and kinetics in marker-based human gait analysis

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ABSTRACT

We developed a Kalman smoothing algorithm to improve estimates of joint kinematics from measured marker trajectories during motion analysis. Kalman smoothing estimates are based on complete marker trajectories. This is an improvement over other techniques, such as the global optimisation method (GOM), Kalman filtering, and local marker estimation (LME), where the estimate at each time instant is only based on part of the marker trajectories. We applied GOM, Kalman filtering, LME, and Kalman smoothing to marker trajectories from both simulated and experimental gait motion, to estimate the joint kinematics of a ten segment biomechanical model, with 21 degrees of freedom. Three simulated marker trajectories were studied: without errors, with instrumental errors, and with soft tissue artefacts (STA). Two modelling errors were studied: increased thigh length and hip centre dislocation. We calculated estimation errors from the known joint kinematics in the simulation study. Compared with other techniques, Kalman smoothing reduced the estimation errors for the joint positions, by more than 50% for the simulated marker trajectories without errors and with instrumental errors. Compared with GOM, Kalman smoothing reduced the estimation errors for the joint moments by more than 35%. Compared with Kalman filtering and LME, Kalman smoothing reduced the estimation errors for the joint accelerations by at least 50%. Our simulation results show that the use of Kalman smoothing substantially improves the estimates of joint kinematics and kinetics compared with previously proposed techniques (GOM, Kalman filtering, and LME) for both simulated, with and without modelling errors, and experimentally measured gait motion.

1. Introduction

Inverse kinematics, the estimation of joint kinematics based on measured trajectories of skin-mounted markers, is complicated by instrumental errors and soft tissue artefacts (STA) (Cappozzo et al., 1996; Chiari et al., 2005; Leardini et al., 2005).

Different techniques to reduce the effect of these errors on the estimated joint kinematics have been proposed (Chiari et al., 2005; Leardini et al., 2005). Spoor and Veldpaus (1980) estimated the positions and orientations of each body segment separately using a segmental optimisation method (SOM). SOM minimises the marker displacement in the segmental reference frame between any two time instants. Lu and O'Connor (1999) used a multi-link model relating the marker positions to the generalized co-ordinates that describe the motion of the body segments along the degrees of freedom (DOFs). At each time instant, their global optimisation method (GOM) estimates all generalized co-ordinates at once from a weighted nonlinear least-squares fit between the measured marker positions and those predicted by the model. GOM outperformed SOM in simulation for a serial three-link model (pelvis, thigh, and shank) joined by two spherical joints (hip and knee), suggesting that imposed joint constraints reduce the effect of errors. Cerveri et al. (2003a, b) used a Kalman filter to estimate joint kinematics. Kalman filtering (KF) is based on a measurement model obtained from the biomechanical model and a process model, which includes prior knowledge about the smoothness of the motion. In addition, the generalized co-ordinates, velocities, and accelerations are estimated simultaneously. Cerveri et al. (2005) proposed local marker estimation (LME), an extension of KF to estimate marker displacements in the segmental reference frames to account for STA. In their simulation study (Cerveri et al., 2005) in which systematic, sinusoidal perturbations added to the three thigh markers modelled STA, LME estimates were at least 50% more accurate than SOM estimates.

KF has two potential advantages over GOM. Firstly, including knowledge about motion smoothness may improve the accuracy of estimated joint kinematics. Secondly, estimating accelerations

Abbreviations: DOF, degree of freedom; GOM, global optimisation method; KF, Kalman filtering; KS, Kalman smoothing; LME, local marker estimation; RMS, root mean square; SOM, segmental optimisation method; STA, soft tissue artefacts

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eliminates the need to differentiate generalized co-ordinates numerically, which can introduce large errors. As these accelerations, in addition to the measured ground reaction forces, are the input for inverse dynamics to calculate joint moments, more accurate joint acceleration estimates will improve the accuracy of joint kinetics. Since Cerveri et al. (2005) did not compare LME with GOM, these advantages have not yet been confirmed.

A drawback of KF is the asymmetrical use of data. At each time instant, estimates are based on the measured marker trajectories up to the considered time instant only. We therefore propose Kalman smoothing (KS) (Rauch et al., 1965), a combination of two filters, to calculate the estimates at each time instant based on the complete marker trajectories. The proposed KS is an extension of the Kalman filter without LME. The purpose of this study was to compare the accuracies of the generalized co-ordinates and accelerations using GOM, KF, LME, and KS using both simulated marker trajectories, with and without modelling errors, and experimentally measured marker trajectories during gait.

2. Kalman Smoothing algorithm

The Kalman smoother (Bar-Shalom and Li, 1993; Rauch et al., 1965) combines prior knowledge, described by a process and measurement model, with the measured marker trajectories to produce an estimate of the joint kinematics while minimising the estimation error statistically. The generalized co-ordinates q and their derivatives up to the Kth order, which describe the joint kinematics, are collected in a vector x:

$$x = [q_1 q_1^{(1)} \ldots q_1^{(K)} q_2 q_2^{(1)} \ldots q_2^{(K)} \ldots q_J q_J^{(1)} \ldots q_J^{(K)}]^{\mathrm{T}},$$

with $j = 1 \ldots J$ indicating the DOF and $q_j^{(k)}$ the kth time derivative of q_j.

The process model describes the expected time evolution of the joint kinematics x and is composed of J submodels describing the motion of each DOF. While the submodels are based on the assumption that the Kth derivative of the generalized co-ordinate $q_j^{(K)}$ is constant, a noise term n_j takes into account the errors introduced by this assumption:

$$\begin{bmatrix} q_j(t_i+\Delta t) \\ q_j^{(1)}(t_i+\Delta t) \\ \vdots \\ q_j^{(K)}(t_i+\Delta t) \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & \dfrac{\Delta t^2}{2} & \dfrac{\Delta t^K}{K!} \\ 0 & 1 & \Delta t & \dfrac{\Delta t^{K-1}}{(K-1)!} \\ & & & \\ 0 & & & 1 \end{bmatrix} \begin{bmatrix} q_j(t_i) \\ q_j^{(1)}(t_i) \\ \\ q_j^{(K)}(t_i) \end{bmatrix} + n_j(t_i),$$

with t is the time, $I = 1 \ldots I$ indicates the time instant, and Δt is the sample time. The $(K+1)$th derivative of the generalized co-ordinate is modelled as zero mean Gaussian noise with covariance $\sigma^2_{K+1,j}$. Therefore, the process noise is given by

$$n_j(t) = N(0, Q_j) \quad \text{with} \quad Q_j = \sigma^2_{K+1,j} G^{\mathrm{T}} G \text{ and}$$
$$G = \begin{bmatrix} \frac{\Delta t^{K+1}}{(K+1)!} & \frac{\Delta t^K}{K!} & \Delta t \end{bmatrix}.$$

The measurement model relates the joint kinematics $x(t)$ to the measured marker positions, collected in $z(t)$. This model is composed of a noiseless measurement model $h(x(t))$ and measurement noise $v(t)$:

$$z(t) = h(x(t)) + v(t)$$

The noiseless measurement model $h(x(t))$ is based on a biomechanical model consisting of ten body segments including 21 DOFs (Fig. 1, Delp et al., 1990). The measurement noise, $v(t)$, is drawn from a zero mean Gaussian distribution and expresses the uncertainty for the marker position measurements.

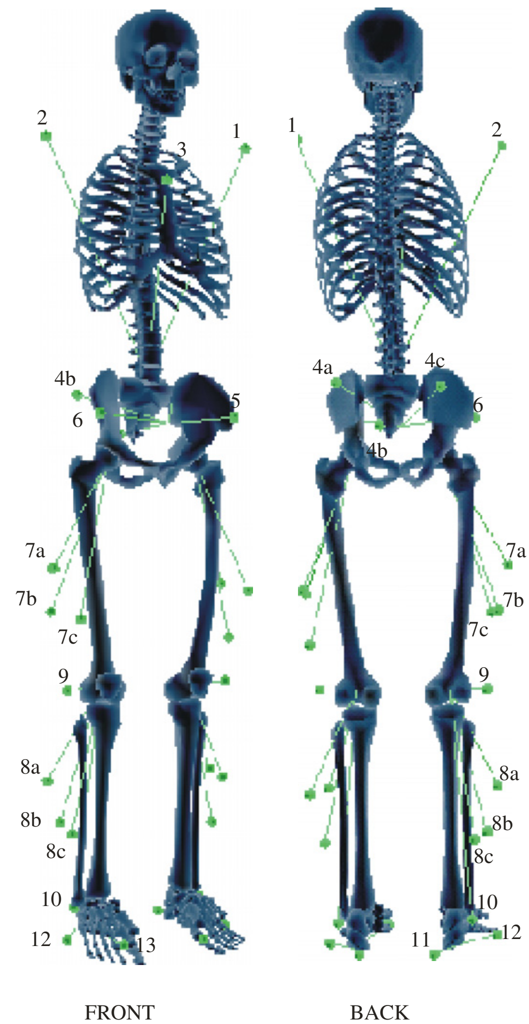

Fig. 1. Biomechanical model and marker placement protocol. The biomechanical model consists of ten body segments: a head–arms–trunk segment, the pelvis, left and right thigh, shank, hindfoot and forefoot (Delp et al., 1990). This model includes 21 DOFs. Spherical joints connect the head–arms–trunk segment to the pelvis and the pelvis to the thighs. The ankle and subtalar joints are modelled as simple hinges, whereas the knee joints are modelled as sliding hinges (Yamaguchi and Zajac, 1989). The remaining six DOFs correspond to the position and orientation of the pelvis. The generic biomechanical model was scaled to the subject's dimensions. A modified Cleveland marker placement protocol (Sutherland, 2002) was used for the data collection. The marker set consisted of 30 markers, including five clusters of three markers. Three anatomical markers defined the trunk: a marker on the lateral aspects of the left (1) and right (2) shoulder and a marker on the sternum (3). The pelvis segment is defined by a cluster of three technical markers on the sacrum (4a–c) and two anatomical markers on the left (5) and right (6) anterior superior iliac spine (ASIS). The thigh segment is defined by a cluster of three technical markers (7a–c). The shank segment is defined by a cluster of three technical markers (8a–c), an anatomical marker on the lateral epicondyle (9), and an anatomical marker on the lateral malleolus (10). The foot segment is defined by three anatomical markers on the heel (11), the lateral foot (12) and the first metatarsal head (13). During a static calibration trial, additional anatomical markers were added to the medial femoral condyles and the medial malleoli to define the knee and ankle joint axis.

KS has two consecutive steps. First, a Kalman filter (Kalman, 1960) estimates the joint kinematics at t_i using only the measured marker trajectories up to t_i. Second, a backward recursion using the measured marker trajectories from the last instant down to t_i, follows the Kalman filter. The resulting Kalman smoother estimates the generalized co-ordinates and their derivatives based on all the information available: the complete marker trajectories, the process model, and the measurement model. An extended