# Ambulatory inertial spinal tracking using constraints


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## ABSTRACT

Wearable inertial sensor networks represent a well-known and meanwhile cheap solution for in-field motion capturing. However, the majority of existing approaches and products rely on simple stick figure models to approximate the human skeleton with only a few rigid segments and connecting joints. Especially the spine is often extremely simplified with one or at most two segments. This simplification results in significant kinematic estimation errors. This paper presents a novel inertial tracking approach, where a recursive filter with integrated constraints enables detailed and efficient estimation of the spine kinematics in real time. The advantages of the proposed approach are confirmed in experiments using ground truth data from an optical reference system.



## Categories and Subject Descriptors

I.2.9 [**Robotics**]: Kinematics and dynamics; I.6.5 [**Simulation and Modeling**]: Model Development

## General Terms

Theory, Algorithms

## Keywords

Inertial motion capture, sensor fusion, body sensor network


## 1. INTRODUCTION

IMUs typically measure 3D linear acceleration, rotation speed and magnetic field. Mounting one IMU on each major limb segment enables rough human motion capturing, which is suitable for various applications, e.g. in the areas of sport assessment [4], robot control [3] and activity recognition [9]. The availability of highly miniaturized, low-energy and low-cost sensors and computing platforms, moreover, make inertial systems affordable, ergonomic, wearable and, thus, an extremely attractive solution for in-field motion capturing [10].

Inertial systems typically estimate human skeletal movement assuming a simple stick figure model, i.e. a kinematic chain with few rigid segments that are connected via joints [1, 12, 13]. These systems are suitable for applications, where low-detail posture information, or limited information concerning specific body parts (e.g. knee or elbow joint angles) are required. However, many applications can benefit from or even require a higher level of detail, especially with respect to complex and flexible body structures, such as the spine. Typical examples are ergonomics and professional sport applications, like boxing, climbing or dancing.

More detailed representations, e.g. for the complex shoulder joints, have already been successfully applied by taking into account correlations between scapulothoracic and glenohumeral motion, known as the scapulohumeral rhythm [1, 6]. However, in [1], these correlations are not consistently integrated into the estimation process. General methods (e.g. projection) for incorporating equality and inequality constraints into recursive filters have been proposed by [5, 11] and applied to simple simulation examples or well-known problems, such as quaternion normalization.

Comparably to the shoulder, the spine is an extremely complex structure. In order to obtain a perfect representation, ultimately, each vertebra should be modeled as a rigid segment with joints in between. Done in a naive way, this would result in a high number of independent degrees of freedom (joint angles) to be estimated and, consequently, anatomical feature movements to be measured. However, taking into account the correlated movement of the spine elements helps making the estimation problem tractable.

Starting from previous work on inertial tracking of arbitrary kinematic chains using an extended Kalman filter (EKF) [8], this paper proposes a high-detail spine model and associated IMU positioning protocol, along with a consistent incorporation of motion correlations (via inter-segment constraints) into the aforementioned EKF framework. As experiments with an optical reference system show, this results in



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more detailed and precise tracking of the spine posture compared to previous approaches, while using the same number of IMUs and still performing in real time.

## 2. PROPOSED SPINE MODEL AND IMU POSITIONING

The spine is divided into vertebrae, whereas an intervertebral disk placed between each vertebra pair allows for relative rotation. This motion is induced by muscles fixed to spinous processes posterior to the vertebral body. The human spine can be split into three major parts, the cervical, thoracic and lumbar curvature.

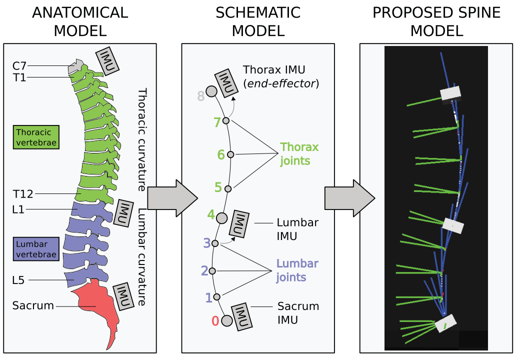



Figure 1: From the anatomical representation with nomenclature (left) to the proposed approximation (right).

Inspired by this anatomy, a kinematic model and IMU positioning protocol for tracking the motion of the latter two curvatures has been developed (cf. Figure 1). Overall, the model is separated into two parts according to the considered curvatures. The flexibility of each curvature is then approximated using four rigid segments connected via joints. This specific amount of Thorax and Lumbar joints proved sufficient for balancing accuracy gain and efficiency of the algorithm, although the approach can easily be extended to an arbitrary number of intermediate joints, due to the generic property of the parameter estimation approach as will be described in the following section.

One IMU is then placed on the Sacrum as reference. Two further IMUs are positioned on the highest vertebrae of the curvatures, i.e. on L1 (Lumbar IMU) and T1 (Thorax IMU). In summary, the proposed kinematic spine model comprises 8 rigid segments connected via 8 ball and socket joints, and 3 IMUs attached to the above mentioned anatomical landmarks are used as measurement sources.

## 3. INERTIAL MOTION CAPTURE SYSTEM

The estimation of the model parameters in terms of joint angles is based on a generic approach for inertial tracking of arbitrary kinematic chains as described in [8]. This approach uses Denavit-Hartenberg (DH) transformations in an EKF framework.

In the following, a fully calibrated system is assumed, i.e. the segment lengths ($d_i$) and IMU poses relative to the spine model ($H_{SI}$) are all known (see e.g. [1]). Furthermore it is assumed that the global frame is given by the Sacrum IMU. The orientation and position of an IMU with respect to the global frame ($H_{GI}$) can be represented via a chain of homogeneous transformations (H) along a path of the kinematic model. E.g. the IMU frame obtained after $n$ preceding angles is given as:

$$H_{GI} = \left[\prod_{i=0}^{n-1} DH(\theta_i)\right] H_{SI}. \tag{1}$$

Here $DH(\theta_i)$ is the DH transformation at joint angle $i$ with variable $\theta$ with the above mentioned calibration parameters already included. In the same way, the position and orientation of an arbitrary point in the kinematic chain can be computed. Note, since the DH formalism allows for only one variable angle per transformation, a ball and socket joint is represented by 3 successive transformations.

The EKF estimates model parameters based on measurements via a predictor-corrector method. It uses a dynamic model, which predicts states, and a measurement model, which corrects the predicted values by incorporating new sensor measurements.

In the proposed approach, the system state comprises the joint angles ($\theta_i$), their velocities ($\dot{\theta}_i$) and their accelerations ($\ddot{\theta}_i$). Defining $\theta = (\theta_0, \ldots, \theta_{n-1})$ and, correspondingly, $\dot{\theta}$ and $\ddot{\theta}$, the state at time $t$ can be summarized as:

$$x_t = (\theta, \dot{\theta}, \ddot{\theta})_t^T \tag{2}$$

containing in total 72 parameters to be estimated.
The dynamic model changes the system state according to a constant angular acceleration model:

$$\begin{pmatrix} \theta \\ \dot{\theta} \\ \ddot{\theta} \end{pmatrix}_{t+\delta} = \begin{pmatrix} I & \Delta & \frac{\Delta^2}{2} \\ 0 & I & \Delta \\ 0 & 0 & I \end{pmatrix} \begin{pmatrix} \theta \\ \dot{\theta} \\ \ddot{\theta} \end{pmatrix}_t + \begin{pmatrix} \frac{\Delta^2}{2} \\ \Delta \\ I \end{pmatrix} v_t, \tag{3}$$

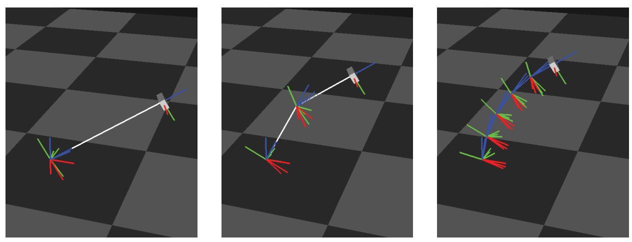
where $v_t$ denotes a white Gaussian process noise matrix and $\delta$ denotes the sample time difference. $I$ is the identity matrix of dimension $n$ by $n$ and $\Delta = \delta I$.

The measurement model is based on forward kinematic equations relating the state variables to the measurements provided by the 3 IMUs (cf. [8] for details).

## 4. CONSTRAINTS

In order to estimate the Thorax (with index set $T$) and Lumbar joint parameters (with index set $L$) based on the measurements of only one IMU per curvature, the correlation between their dynamics is modeled via equality constraints using a similar approach to [11].

The key assumption of this work is that a spinal curvature's motion is equally distributed over each vertebra with respect to the corresponding axis of rotation. An illustration can be found in Figure 2. Hence, it is assumed that



(a) One segment. (b) Two segments. (c) Five segments.

Figure 2: Equal distribution of total rotation through chains.

the angles, and due to their additive behavior, also the angular velocities and angular accelerations are equal within a curvature. This can be modeled as equality constraint:

$$0 = x_{t,k} - x_{t,l} \tag{4}$$

for a pair of states $k \neq l$ with $k, l \in L$ or $T$ respectively. For example, consider the state vector $x_t$ covering the spine model with 8 joints[1], having the index set $S = \{0, \ldots, 7\}$. The constraints apply to $L = \{0, 1, 2, 3\}$ and $T = \{4, 5, 6, 7\}$. Taking for instance the constraints w.r.t. the Lumbar joints ($L$), the corresponding states are extracted from $x_t$, indexed by ($L \subset S$) and denoted by $x_t^L$. The above mentioned constraint model can now be written as:

$$0 = Hx_t^L,\ H = \begin{pmatrix} I & -I & 0 & 0 \\ I & 0 & -I & 0 \\ I & 0 & 0 & -I \end{pmatrix}, \tag{5}$$

and analogously for the Thorax joints. Since (5) has the typical form of a linear (implicit) measurement equation, it can be easily incorporated into the EKF measurement model. The degree, to which the constraint should be taken into account, can be controlled via an additional noise term.

# 5. EVALUATION

The proposed approach is evaluated in 3 experiments using Trivisio[2] ColibriWireless IMUs. Two experiments evaluate the precision, also in comparison to commonly used simple stick figure models, based on ground truth from a validated optical tracking system (cf. [2]). A third experiment compares the proposed approach with a naive solution, where one IMU is used to measure the independent motion of each rigid segment in the spine model. For positioning the IMUs, anatomical landmarks were marked by a medical doctor. Moreover, the segment lengths were measured along the skin.

Figure 3: Experimental setups: Precision setup with markers for optical reference (left) and approximation validation with 9 IMUs (right).

The experimental setup for assessing the precision is shown in Figure 3 (left). A single optical marker was placed on each modeled spine joint, while rigid marker bodies were attached to the IMUs. Optical and inertial reference frames were aligned based on the Sacrum IMU and attached marker body using a standard hand-eye calibration method.

The precision of the proposed approach was compared to two commonly used simple stick figure approaches modeling the spine with one and two segments, respectively. For all approaches, the T1 position was compared to the optical reference. Note that small errors are expected for all approaches due to currently uncompensated soft tissue artifacts and due to the positioning of the IMUs and markers behind the spinous processes. The resulting distance to the actual rotation center was neglected for a fair comparison of the three approaches. As the results in Figure 4 show, the

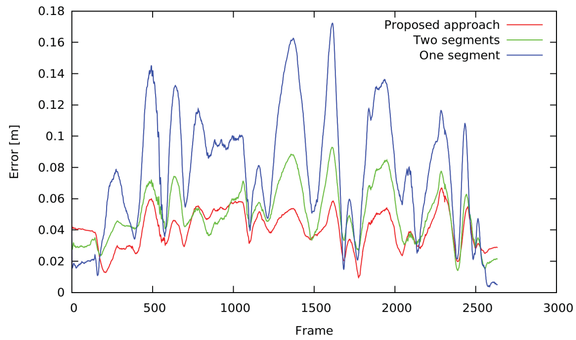



Figure 4: Estimation errors of the T1 position during flexible motion.

proposed and the two segment approach both clearly outperform the one segment approach. Moreover, when comparing the former two, the proposed approach is always more precise when actual motion is involved.

In a second experiment, the precision of the proposed approach was evaluated in more detail, considering the estimation errors of all modeled joint positions (cf. Figure 1). Figure 5 shows an expected error increase from the Sacrum

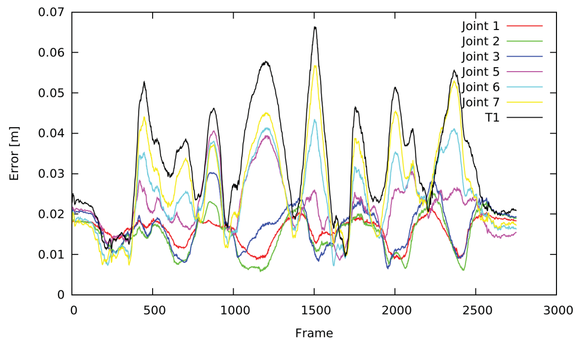



Figure 5: Estimation errors of all joint positions modeled in the proposed approach.

towards T1. This results from the angle estimation errors propagating through the kinematic chain. However, the error stays roughly around 2 cm for all Lumbar joints. Notably, no significant error increase is visible here and the systematic error can be partly contributed to the above mentioned known issues. This confirms a very good correlation between the actual and the estimated motion of the Lumbar curvature.

The Thorax joint positions show comparably higher estimation errors, as expected due to the error propagation, but also a more significant error increase towards T1. The latter indicates that further investigation is required for sufficiently approximating the thoracic curvature's flexibility. At the same time, the proposed approach still clearly outperforms commonly used simple stick figure models, as shown in the first experiment.

The experimental setup for the third experiment is shown in Figure 3 (right). Here, an IMU was attached to each rigid segment of the proposed spine model resulting in a total of 9 IMUs. The proposed approach (constrained es-

[1]For simplicity, here we assume revolute joints.
[2]http://www.trivisio.com/

| Sequence | Mean [$cm$] | Std [$cm$] | Max[$cm$] |
|---|---|---|---|
| Slow | 2.13 | 0.9853 | 5.3707 |
| Fast | 2.14 | 1.3808 | 7.2160 |
| Flexible | 2.59 | 2.00 | 8.0456 |

Table 1: Differences in estimated T1 positions over 3 sequences: The proposed approach based on 3 IMUs is compared to unconstrained estimation with 9 IMUs.

timation based on measurements from 3 IMUs) was then compared to the classical approach (unconstrained estimation based on measurements from 9 IMUs) in three data sequences (with slow, fast, particularly flexible movements), while both used the proposed kinematic spine model. The results in Table 1 show the differences in the estimated T1 positions (end-effector). For extremely flexible movements, the maximal differences increase to about 8 cm indicating the limitations of the thoracic curvature approximation already pointed out above. However, overall, a mean error only slightly above 2 cm for all sequences, shows a very good correlation between the trajectories. Hence, it can be concluded that with the proposed constrained approach much fewer measurement points are needed for providing comparable precision. This result enables more efficient estimation, as well as, higher wearing comfort due to a reduced number of required IMUs.

# 6. CONCLUSION

This paper presents an inertial motion capturing approach for more detailed and precise tracking of the spine posture compared to previous approaches, while still using the same number of IMUs and performing in real time.

Inspired by the anatomical structure of the human spine, a detailed kinematic model and IMU positioning protocol was developed. An existing system for inertial tracking of arbitrary kinematic chains was then enhanced with inter-state equality constraints, which model the correlated motions of the spine segments. This approach provides the above mentioned advantages, as has been evaluated using an optical reference system.

At the same time, the experiments show a clear need for further research. E.g. the assumption of the IMUs sitting in the rigid segments (bones), as well as, well-known soft tissue (clothing, skin) effects result in a systematic estimation error. This can be overcome by calibrating for or even continuously estimating the position offsets of the IMUs with respect to the segments they are attached to. Another approach is to transfer concepts from the optical motion capturing domain, such as cluster markers [7], for error compensation. This would, however, require more IMUs being attached to one segment.

Finally, while this paper applies inter-state equality constraints specifically to the problem of spine posture estimation, the overall concept can be enhanced to more complex types of constraints for consistently modeling a number of other anatomical conditions, such as the aforementioned scapulohumeral rhythm or posture dependent joint angle limits.

# 7. ACKNOWLEDGMENTS

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