Estimation of the Knee Flexion-Extension Angle During Dynamic Sport Motions Using Body-worn Inertial Sensors

Carolin Jakob[1]
carolin.jakob@medtech.stud.uni-erlangen.de

Patrick Kugler[1]
patrick.kugler@cs.fau.de

Felix Hebenstreit[1,2]
felix.hebenstreit@cs.fau.de

Samuel Reinfelder[1]
samuel.reinfelder@cs.fau.de

Ulf Jensen[1]
ulf.jensen@cs.fau.de

Dominik Schuldhaus[1]
dominik.schuldhaus@cs.fau.de

Matthias Lochmann[2]
matthias.lochmann@sport.uni-erlangen.de

Bjoern M. Eskofier[1]
bjoern.eskofier@cs.fau.de

[1]Digital Sports Group, Pattern Recognition Lab, Department of Computer Science
[2]Institute of Sport Science and Sport
Friedrich-Alexander-University Erlangen-Nuremberg, Germany

ABSTRACT

Motion analysis has become an important tool for athletes to improve their performance. However, most motion analysis systems are expensive and can only be used in a laboratory environment. Ambulatory motion analysis systems using inertial sensors would allow more flexible use, e.g. in a real training environment or even during competitions.

This paper presents the calculation of the flexion-extension knee angle from segment acceleration and angular rates measured using body-worn inertial sensors. Using a functional calibration procedure, the sensors are first aligned without the need of an external camera system. An extended Kalman filter is used to estimate the relative orientations of thigh and shank, from which the knee angle is calculated.

The algorithm was validated by comparing the computed knee angle to the output of a reference camera motion tracking system. In total seven subjects performed five dynamic motions: walking, jogging, running, jumps and squats. The averaged root mean squared error of the estimated knee angle was $8.2^\circ \pm 2.4^\circ$ over all motions, with an average Pearson-correlation of 0.971 ± 0.020.

In the future this will allow the analysis of joint angles during dynamic sports movements.

Keywords

inertial sensors, feedback training, sports, joint angles, motion tracking, Extended Kalman Filter, Euler angles

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1. INTRODUCTION

Motion analysis has become an important tool, which can contribute to the performance of an athlete [11]. It obtains an objective characteristic of the motion, which is used to generate qualitative feedback. Thereby, the performance of the athlete can be improved while injuries can be avoided [16].

The analysis of athletes performance is usually done with a camera motion tracking system in a laboratory environment [11]. It is seen as the gold standard because of its high accuracy. However, the camera motion tracking system is expensive and motion is performed in an artificial environment, e.g. on a treadmill [16]. The disadvantages of a camera motion tracking system can be overcome with inertial sensors. An inertial measurement system is ambulatory, cheap and motion analysis can be performed outside a lab in a real training environment or even during competition [18]. Through their low power consumption, even long term observations are possible [8] and such systems have been used for medical applications [12].

A set of three-dimensional accelerometers attached on the human body can be used as an inclinometer to measure the orientation of sensors with respect to gravity [22], [10]. With the use of models, joint angles can be estimated. The accuracy is less for motions with relatively large accelerations. Three-dimensional gyroscopes can be incorporated to improve the accuracy [15], [6], [23]. The angular rates measured by the gyroscopes are integrated to estimate the change of orientation. However, over time, large integration error can accumulate. The accelerometer in combination with the gyroscope can be used to compensate the drifts and to define an absolute orientation [6]. Besides deterministic approaches as TRIAD (Tri-axial attitude Determination) and QUEST (Quaternion Estimator) , the preferred choice to fuse measurements of accelerometer and gyroscope and to estimate human body orientation with a high accuracy is a stochastic approach, the Kalman Filter [18].

Estimation of the three-dimensional orientation of body segments using inertial sensors in combination with magnetic sensing, including a three-dimensional accelerometer, a three-dimensional gyroscope and a three-dimensional magnetometer, is available in research [18] and for commercial systems [17]. In such a measurement system, the accelerometer is used to detect inclinations, the gyroscope to detect fast changes and the magnetometer to measure a horizontal reference direction. Unfortunately, the measurements of the magnetometer can be distorted in the proximity of ferromagnetic materials [16].

The calibration of the sensors attached on the human body can be done using an external system, i.e. a camera motion tracking system [3] or a stereoscopic camera [21]. Favre *et. al* [5] proposed an alignment procedure of sensors without the need of an external system. Two alignment motions are used to align the sensors vertically and horizontally. However, they did not apply their method to highly dynamic sport motions, e.g. jumping.

The usage of inertial-based joint angle determination system in the fields of sports is still an unexplored research area. Chardonnes *et. al* [1], e.g. established an application of inertial sensor and knee angle determination in alpine sports. An inertial sensor mounted at the ankle was used during running in [19] to classify different running surfaces and inclinations. Downling *et. al* [4] investigated the improvement of motions through feedback by inertial sensing for avoiding anterior cruciate ligament injury and Cooper *et. al* [3] evaluated an inertial-based knee angle estimation approach for slow jogging. The estimation of the knee angle in running and further dynamic motions is still unexplored [8].

The purpose of this paper is to investigate the performance of an inertial-based orientation estimation approach in highly dynamic motions. As the application is the usage in sports, the alignment of sensor frames should be achieved without the usage of an external system. The idea of Favre *et. al* [5] is used for calibration and the orientation estimation is done using an extended Kalman filter. As an example for an important joint, we will focus on determining the knee angle using an accelerometer and gyroscope attached to both the thigh and shank. In the following sections we give details on the used inertial measurement system, present the proposed algorithm for estimation of the joint angle and evaluate our system in an extensive study involving multiple dynamic motions.

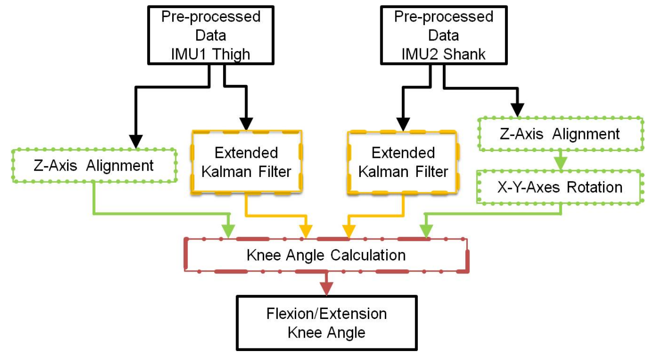

Figure 1: An overview of the calculation of the knee angle from the two IMUs at the tigh and shank. The procedure can be divided into three main steps: the alignment procedure, the extended Kalman filter, and the knee angle calculation.

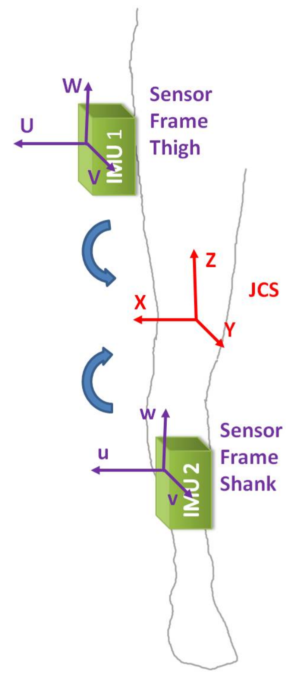

Figure 2: Two inertial measurement units are placed on the thigh and shank, which form their own local coordinate system. To compute the joint angle, the sensor frames are transformed in a mutual coordinate system, the joint coordinate system (JCS).

2. METHODS

The next sections outline the proposed method for calculating the flexion/extension knee angle from inertial sensor data. First, we describe how the sensors are placed and which coordinate systems are used to describe the joint motion. Then we describe the algorithm for computing the knee angle, which consists of three main parts. First the sensor frames are aligned using a functional alignment procedure. As a second step, an extended Kalman filter (EKF) estimates the relative orientation of each IMU. Finally this information is combined in the flexion/extension knee angle calculation step. Figure 1 illustrates the main concept of the knee angle estimation presented in this paper.

2.1 Description of Joint Motion

For the calculation of the knee angle we assume that two IMUs containing 3D accelerometers and 3D gyroscopes are attached to the thigh and shank (see Figure 2), forming two sensor frames UVW and uvw. The knee joint is described as recommended by the international society of biomechanics in a mutual coordinate system, the so called joint coordinate system (JCS) as defined by Grood and Sunday [9]. For each sensor attachment the transformation from the initial sensor frames into the JCS and the resulting alignment of sensor is done using the idea of the functional alignment procedure of Favre *et. al* [7].

The joint motion is determined by the orientation of each segment and is described in the XYZ-Euler angle representation. The rotation matrix that transforms the sensor frame at any time step into the initial sensor frame is defined by the multiplication of the single rotation matrices around each axis and is determined by

$$R_i = \begin{bmatrix} c\theta\ c\psi & -c\theta\ s\psi & s\theta \\ c\phi\ s\psi\ +\ s\phi\ s\theta\ c\psi & c\phi\ c\psi\ -\ s\phi\ s\theta\ s\psi & -s\phi\ c\theta \\ s\phi\ s\psi\ -\ c\phi\ s\theta\ c\psi & s\phi\ c\psi\ +\ c\phi\ s\theta s\psi & c\phi\ c\theta \end{bmatrix} \quad (1)$$

where c and s denotes the cos and sin function and ϕ, θ, and ψ are the rotation angles about the $U-$, $V-$, and $W-$axes, respectively [24].

2.2 Alignment of Sensor Frames

The alignment procedure is divided into two steps. The sensor frames of the thigh and shank are first aligned vertically with the JCS (Z-axis alignment). Then, the sensor frame of the shank is rotated around the Z-axis to be aligned horizontally with the sensor frame of the thigh (XY-rotation).

For the vertical alignment, the inertial data of the accelerometer from the motion still standing is required, where the subject stands still with straight legs for ten seconds. As the gravity is prominent in the signal of accelerometers during static conditions [14], the averaged gravitational vector g is detected for each sensor frame. It is used to calculate the rotation matrices R_{Z1} and R_{Z2}, which align the vertical components W and w, respectively, with the vertical axis of the JCS, Z. Z is defined by $(0,0,1)^{\mathrm{T}}$. Each rotation matrix is computed by [2]

$$R_Z = \begin{bmatrix} k_x k_x v\alpha + c\alpha & k_x k_y v\alpha - k_z s\alpha & k_x k_z v\alpha + k_y s\alpha \\ k_x k_y v\alpha + k_z s\alpha & k_y k_y v\alpha + c\alpha & k_y k_z v\alpha - k_x s\alpha \\ k_x k_z v\alpha - k_y s\alpha & k_y k_z v\alpha + k_x s\alpha & k_z k_z v\alpha + c\alpha \end{bmatrix}$$

where α is the misalignment angle between g and $(0,0,1)^{\mathrm{T}}$ and k the rotation axis, which is the three-dimensional perpendicular unit vector to g and $(0,0,1)^{\mathrm{T}}$. The abbreviations s and c symbolize the sin and cos functions, and $v = 1 - \cos(\alpha)$.

For the horizontal alignment the motion AA-rotation as defined by Favre *et. al* [5], is required. The straight leg is lifted up and down laterally for 20 seconds, which produces an approximately constantly orientated angular rate vector in the sensor frame of thigh and shank. The misalignment angle of the detected angular rate vectors ω^1 and ω^2 in the sensor frame of thigh and shank are used to form the rotation matrix R_{XY}, which rotates the sensor frame of the shank around the already aligned Z-axis to align it with the sensor frame of the thigh. For each time step k, ω^1 and ω^2 are projected on the UV- and uv-plane, respectively. The misalignment angle β_k of the projected angular rate vectors is first calculated for each time step by the cosine function and then averaged with the weighting function according to Favre *et. al* [5] by

$$\beta = \frac{\sum_{k=1}^{N} ||(\vec{\omega}^1_{k,x}\vec{\omega}^1_{k,y})^{\mathrm{T}}|| \quad \beta_k}{\sum_{k=1}^{N} ||\vec{\omega}^1_k||} \ . \quad (2)$$

N is the amount of time steps. β is the weighted averaged misalignment angle and is used to compute the rotation matrix R_{XY} by

$$R_{XY} = \begin{bmatrix} \cos(\beta) & -\sin(\beta) & 0 \\ \sin(\beta) & \cos(\beta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \ . \quad (3)$$

2.3 Extended Kalman Filter

Two similarly designed standard EKF are used to describe the roll and pitch orientation of the two adjacent segments. The EKF is designed with an eight-row state vector as

$$\vec{x} = \begin{pmatrix} \vec{a} \\ \vec{\omega} \\ \phi \\ \theta \end{pmatrix}, \quad (4)$$

containing the three-dimensional acceleration $\vec{a}$ of the accelerometer, the three-dimensional angular rates $\vec{\omega}$ of the gyroscope, both expressed in the three axes of the sensor frame, and the roll ϕ and pitch θ orientation angles. The rotation between the initial frame and the sensor frame at a time step k is defined by the three Euler angles ϕ, θ and ψ. For the calculation of the flexion/extension knee angle only the components roll and pitch are needed.

The dynamic system f is modeled linearly as

$$f = \begin{cases} f_{1-3}: & \vec{a}_k = \vec{a}_{k-1} + \vec{u}^a_{k-1} \\ f_{4-6}: & \vec{w}_k = \vec{w}_{k-1} + \vec{u}^w_{k-1} \\ f_7: & \phi_k = \phi_{k-1} + \Delta t\ \dot{\phi}_{k-1} \\ f_8: & \theta_k = \theta_{k-1} + \Delta t\ \dot{\theta}_{k-1}\ , \end{cases} \quad (5)$$

where k indicates the time step, Δt denotes the time interval between each time step, $\vec{u}^a$ and $\vec{u}^w$ are the vectors of noise on acceleration and angular rates, and $\dot{\phi}$ and $\dot{\theta}$ denote the time derivatives of ϕ and θ.

Angles are calculated from the angular rates using the Euler formulation. In evaluations of the presented knee angle algorithm, it was seen that the yaw component of the gyroscope angular rate vector is the main reason for drifts in the outputs of the EKF. Therefore, in the calculation of orientation angles the assumption is made that the gyroscope yaw axis is zero. Setting ω_ψ=0, f_7 and f_8 are estimated by

$$f_7: \quad \phi = \phi_{k-1} + \Delta_t\ [\omega_\phi + \tan(\theta)\ \omega_\theta \sin(\phi)] \quad (6)$$

$$f_8: \quad \theta = \theta_{k-1} + \Delta_t\ [\omega_\theta \cos(\phi)]\ . \quad (7)$$

The observations of the dynamic system are the three-dimensional acceleration of the accelerometer and the three-dimensional angular rates of the gyroscope, which are both measured in the sensor frames of thigh and shank. The measurement is described by

$$\vec{h}_k = \begin{pmatrix} \vec{a}_k \\ \vec{\omega}_k + \vec{b} \end{pmatrix} + \vec{v}_k, \quad (8)$$

where $\vec{v}$ is the measurement noise. The output of the gyroscope is defined by the angular rate vector $\vec{\omega}$ and by the bias $\vec{b}$, which is assumed to be constant for each trial and is determined for each axis to be the average value of angular rates over the time steps of each trial. This assumption is based on the cyclical behavior of movements.

The measurement and process noise covariance matrices are defined by

$$Q = \begin{bmatrix} \sigma^a_u\ Id_3 & 0_{3\times3} & 0_{3\times2} \\ 0_{3\times3} & \sigma^\omega_u\ Id_3 & 0_{3\times2} \\ 0_{2\times3} & 0_{2\times3} & 0_{2\times2} \end{bmatrix} \ . \quad (9)$$

and

$$R\ =\ r\ Id_{6\times6}\ . \quad (10)$$

Id denotes the identity matrix and σ^a_u, σ^ω_u, and r are parameters of the algorithm.

2.4 Flexion/extension Knee Angle Calculation

The flexion/extension knee angle is defined in the sagittal plane of the leg and is the intersection angle of the vertical component of the sensor frame of thigh and shank.

The relative orientation of segments over time is estimated by the EKF, where the orientation is based on the initial sensor frame. To calculate the transformation matrix of each sensor frame at any time step into the initial sensor frame, R_i, as determined in equation (1), is used. The vertical component of the sensor frames for each time step expressed in the initial sensor frames is then calculated using the roll and pitch component estimated by the EKF by

$$r_k^{i1} = R_i \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} \sin(\theta_k^1) \\ -\sin(\phi_k^1)\ \cos(\theta_k^1) \\ \cos(\phi_k^1)\ \cos(\theta_k^1) \end{pmatrix} \tag{11}$$

for the thigh and

$$r_k^{i2} = R_i \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} \sin(\theta_k^2) \\ -\sin(\phi_k^2)\ \cos(\theta_k^2) \\ \cos(\phi_k^2)\ \cos(\theta_k^2) \end{pmatrix}, \tag{12}$$

for the shank.

The vertical component expressed in the initial sensor frames can further be transformed in the JCS using the vertical and horizontal alignment matrices R_{Z1}, R_{Z2}, and R_{XY}. Describing the whole transformation, the vertical component of the sensor frames at any time step can be described with ϕ and θ based on the JCS as

$$r_k^1 = R_{Z1}\ R_k^{i1} \tag{13}$$

$$r_k^2 = R_{XY}\ R_{Z2}\ R_k^{i2} \tag{14}$$

The flexion/extension knee angle for each time step is calculated by projecting r^1 and r^2 for each time step on the X-Y-plane and determining the intersection angle by

$$\eta_{knee} = \bar{s}\ \arccos\left(\frac{\begin{pmatrix} r_{y,k}^1 \\ r_{z,k}^1 \end{pmatrix} \circ \begin{pmatrix} r_{y,k}^2 \\ r_{z,k}^2 \end{pmatrix}}{\left\| \begin{pmatrix} r_{y,k}^1 \\ r_{z,k}^1 \end{pmatrix} \right\| \ \left\| \begin{pmatrix} r_{y,k}^2 \\ r_{z,k}^2 \end{pmatrix} \right\|} \right), \tag{15}$$

where $\bar{s} = \text{sign}(r_{y,k}^2\ r_{z,k}^1 - r_{z,k}^2\ r_{y,k}^1)$ defines the sign of rotation and $\circ$ denotes the dot product. The estimated flexion/extension knee angle η_{knee} is the final result of the presented joint angle calculation method.

3. EXPERIMENTAL VALIDATION

3.1 Inertial Measurement System

For evaluating the presented algorithm, two inertial measurement units (IMU) (Invensense, Sunnyvale, CA, USA) containing an accelerometer ($\pm$ 16 g) and a gyroscope ($\pm$ 2000 $^\circ$/s) were attached to the thigh and the shank of the right leg. Double-adhesive tape was used to attach the sensors to the skin or tight trousers, causing a reasonable firm attachment to the segments. The position of the measurement units was selected with proximity to bones to minimize artifacts through muscle movements. A data logger was attached on the thigh and allowed recording inertial data from both sensors on a SD-card at 1000 Hz. Figure 3 shows the exact positioning of sensors.

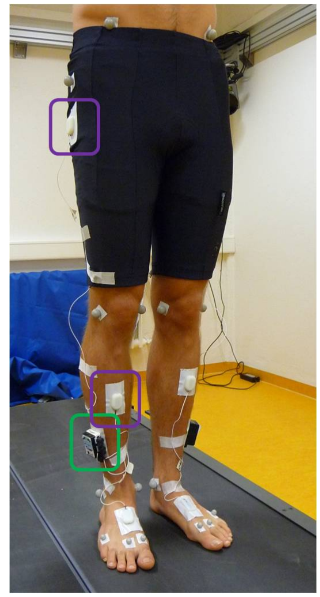

Figure 3: Attachment of the IMUs (top and middle box) and the data logger (bottom box) during data collection. The IMU of the shank was positioned four centimeters under the trochanter major, while the IMU of the thigh was positioned four centimeters under the middle of the frontal tibia. For the reference system, 32 reflective markers were attached to the leg.

3.2 Reference Measurement System

The gold standard in motion analysis is the usage of an camera motion tracking system, which tracks reflective markers over time. Therefore, as reference to the inertial-based knee angle, a camera motion tracking system with eight camaras was used (Qualysis, Göteborg, Sweden). The reference knee angle was calculated using Visual 3-D Reader (C-Motion, Germantown, Maryland, USA) at 200 Hz. The attachment of reflective markers can be seen in Figure 3. The camera system and the inertial sensor recorder were synchronized by a wireless trigger system with high accuracy and low jitter [13]. Any remaining systematic time offset between the two systems was removed before performing the evaluation.

3.3 Study Design

The study was conducted at the Motion Lab of the FAU Erlangen-Nuremberg and was approved by the local ethics committee. Informed consent was obtained from the test subjects. In total, seven subjects participated in the study. Their anthropometric data is presented in Table 1. The study contained seven motions. For the vertical alignment of sensors the subject stood still for ten seconds. The AA-rotation, where the right leg is lifted up and down laterally, was used for the horizontal alignment of sensors. The additional motions were walking, jogging, running, squats, and countermovement jumps. These five dynamic motions differ in speed and magnitude of the change of the knee angle and were used to evaluate the knee angle calculation algorithm during dynamics. All motions were performed on a two-belt treadmill to simplify execution. Some data had to

Anthropometric data general	
Number of Subjects	7
Female	4
Male	3
Age (year)	25 ± 3
Height (cm)	178 ± 13
Weight (kg)	75 ± 14

Table 1: The anthropometric data of the test subjects (mean ± standard deviation).

Number of test data	
Still Standing	7
AA-Rotation	7
Walking 1.3 m/s	7
Jogging 2.2 m/s	7
Running 3.0 m/s	5
Squats	6
Jumps	6

Table 2: Number of test data used for the evaluation of each dynamic motion. The test data includes the inertial data of accelerometer and gyroscope attached on the thigh and shank.

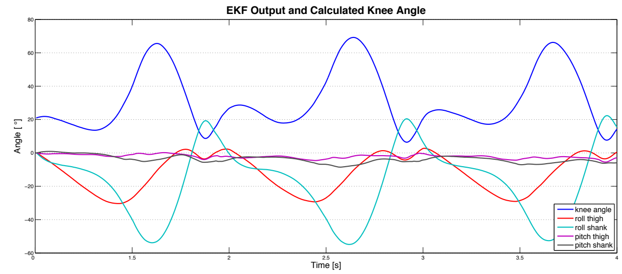

Figure 4: Flexion/extension knee angle calculated using the outputs of the EKF roll and pitch of thigh and shank during walking at 1.3 m/s.

Dynamic motion	RMSE in ° mean ± std	Correlation mean ± std
Walking 1.3 m/s	7.0 ± 1.7	0.968 ± 0.020
Jogging 2.2 m/s	7.3 ± 1.7	0.965 ± 0.021
Running 3.0 m/s	10.2 ± 3.4	0.956 ± 0.035
Squats	9.7 ± 2.0	0.976 ± 0.016
Jumps	7.0 ± 2.9	0.991 ± 0.006

Table 3: Average and standard deviation of RMSE and Pearson-correlation for dynamic motions.

be excluded due to missing or incomplete sensor data. The number of test data used for evaluation for each motion is listed in Table 2.

3.4 Evaluation of the Knee Angle

The inertial sensor based estimated flexion/extension knee angle was evaluated on all five dynamic motions in comparison to the camera motion tracking system. The parameters σ_u^a, σ_u^ω, and r were determined systematically in comparing the resulting knee angle of different parameter combinations for a single subject. The optimal parameter combination was chosen to have the highest Pearson-correlation of the resulting knee angle in comparison to the camera system as reference.

The root mean squared error (RMSE) and the Pearson-correlation was then computed for ten seconds. To remove any systematic amplitude offset between both systems, the knee angle outputs were aligned before the evaluation was performed. In order to compare the performance of the presented knee angle calculation algorithm, the of the two systems were aligned before parameter computation. This amplitude shift was calculated by averaging the position of minima in the angle data and calculating the average offset between inertial and reference system. Thereby, a systematical offset, which could be caused by imperfect attachment of the sensors, is not considered in the evaluation.

4. RESULTS

Figure 4 illustrates the knee angle calculation using the outputs of the EKF for the data set walking with 1.3 m/s.

The parameter search resulted in $\sigma_u^a = 100$, $\sigma_u^\omega = 1100$, and $r = 1000$. The results of the evaluation of all subjects are shown in Table 3, where the RMSE and Pearson-correlation are averaged over the results of number of available test data. The mean RMSE and mean Pearson-correlation, both averaged over the average of the dynamic motions were 8.2° and 0.971 with a mean standard deviation of 2.4° and 0.020, respectively. In Figure 5, the knee angles estimated from the inertial measurement system and the camera system are compared for one subject performing the different motions.

5. DISCUSSION

This study demonstrated an algorithm to compute the knee flexion-extension angle from two body-worn inertial sensors. The extended Kalman filter, which is often used in the literature for human motion analysis [18] was adapted to highly dynamic motions and combined with a functional alignment procedure [5] for aligning sensor frames without the need of an external camera system.

During the validation the inertial-based knee angles was estimated over a 10 second period with an mean RMSE and mean Pearson-correlation of 8.2° ± 2.4° and 0.971 ± 0.020. This shows that the presented algorithm allows to obtain sufficiently accurate knee angle estimates from body-worn inertial sensors, even during high dynamic motions. The estimated knee angles correlated with a high accuracy, even for the highly dynamic jumps. This means that the detection of fast changes that are small is achieved precisely.

Regarding the accuracy of the knee angle estimation and the usage of the inertial-based estimation procedure in sports, the presented algorithm cannot be used as a tool in comparing motion pattern of different athletes to each other or a camera reference system, as the accuracy is to low. Further improvement regarding the constancy for different speed is compulsory. As the error of the estimated knee angle to the reference system stays acceptably constant over each speed the presented knee angle estimation tool could be used to analyse and optimize the motion pattern of one athlete individually for one selected speed. Moreover, the presented

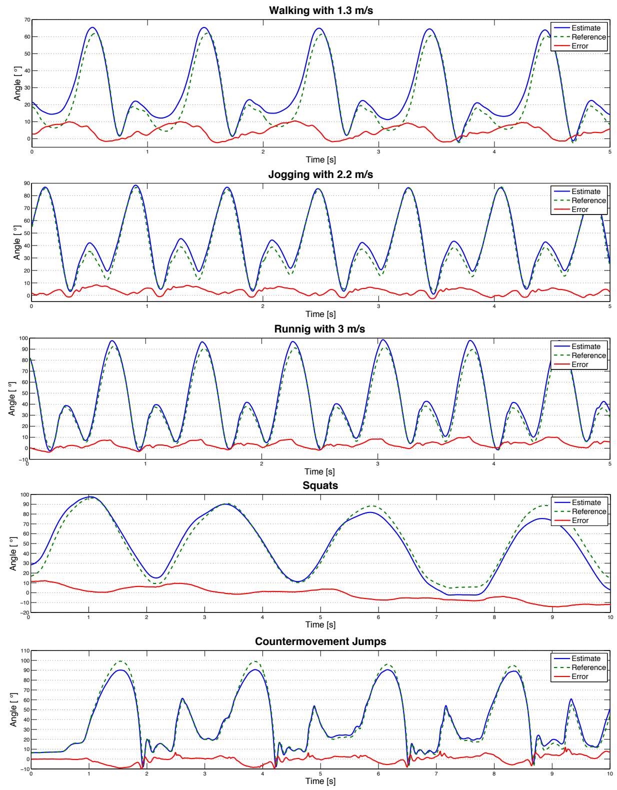

Figure 5: Knee angles computed by the algorithm compared to the camera reference knee angles from the camera system for one subject performing all five dynamic movements. Additionally the knee angle estimation error is shown.

knee angle estimation tool could still be used to track average values of the biomechanics of the motion over time.

Other researcher have investigated the inertial-based knee angle calculation during relatively slow motions [20], [21], [7], Cooper *et. al* [3] evaluated their work on running with 2.2 m/s with a RMSE of 3.4°, which is better than the presented algorithm. However, in contrast to the algorithm presented in this paper, Cooper based the alignment of sensor frames on a camera system. This improved the resulting knee angle, but is critical regarding the usage of inertial measurement units in a real environment in the field of sports. In contrast, the presented algorithm relies on the functional alignment procedure presented by Favre *et. al* [5]. This allows the estimation of the joint angle without any initialization from a reference system.

Most ambulatory three-dimensional orientation measurement systems include accelerometers, gyroscopes, and magnetometers [18], [17]. However, none of these studies reported on the error of the determination of the knee angle during dynamic motions. Favre *et. al* [5] calculated the flexion/extension angle based on repeated alignment motions trials with an error less then 3°. However, their results were only based on slow walking and was not evaluated on high dynamic motions. As the parameters of the presented algorithm were optimized for dynamic motions, the presented algorithm could not achieve such a high accuracy during walking. However, the accuracy was quite stable even during highly dynamic motions, e.g. jumping. A further optimization of the algorithm parameters to the motion task will be subject of future work.

While the presented algorithm had a very high correlation for all motions, it could not achieve an RMSE error below 7 °, which is higher than errors reported by other approaches. However, the accuracy of the presented algorithm is sufficient for many tasks and applications, e.g. feedback training or performance evaluation. Due to the high correlation, the error is most probably caused by systematic offsets or by drift. During the evaluation it was also found that the accuracy decreased with increasing speed. Again, the main reason might the increasing drift and inaccuracy of the gyroscope when measuring large angular rates. Furthermore, stronger vibration of muscles can produce additional noise in sensors and distort the attachment of sensors on the leg. Both problems could be solved by incorporating a bias term in the EKF. Additionally one could incorporate prior knowledge about the motion. This could be used to detect steps and to reset the angle calculation after each stride.

One important limitation of the presented work is the stability of the EKF in the trials with highly dynamic motions. During the experiments the EKF was found as stable, but the stability is still dependent on the chosen parameters and dynamics. This means that the estimation of knee angles in even higher dynamic motions, as during soccer could produce instabilities. Then the parameter of the EKF would have to be adopted to the dynamic motion and an automatic adjustment of the parameters might become necessary. This will be investigated in future work.

To our knowledge, this is the first study presenting and evaluating the estimation of knee joint angles from inertial-sensors with the purpose of the usage in dynamic sports. We believe it is a further step towards the usage of inertial-based motion analysis during sport applications.

6. SUMMARY

This paper presented an inertial sensor based knee angle calculation algorithm usable in the novel application field of running sports. Knee angles are estimated with an extended Kalman filter using the data of accelerometer and gyroscope both attached on the thigh and shank. The calibration of sensors is done without the usage of an external system. The paper presented an important step towards the application of inertial-sensors for analysis of joint angles in sports. Using the algorithms presented in this paper, objective feedback of motions can be obtained from the inertial sensors. This could constantly help improving the performance of the athlete in training or even in competitions.

7. ACKNOWLEDGMENTS

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