# Motion Capturing with Inertial Measurement Units and Kinect
## *Tracking of Limb Movement using Optical and Orientation Information*

Christoph Kalkbrenner, Steffen Hacker, Maria-Elena Algorri and Ronald Blechschmidt-Trapp
*Insitute of Medical Engineering, University of Applied Science Ulm, Albert-Einstein-Allee 55, 89075 Ulm, Germany*

Keywords: Motion Analysis, Inertial Measurement Unit, IMU, Motion Tracking, Kinect, Data Fusion, Kalman Filter.

Abstract: This paper presents an approach for the tracking of limb movements using orientation information acquired from Inertial Measurement Units (IMUs) and optical information from a Kinect sensor. A new algorithm that uses a Kalman filter to fuse the Kinect and IMU data is presented. By fusing optical and orientation information we are able to track the movement of limb joints precisely, and almost drift-free. First, the IMU data is processed using the gradient descent algorithm proposed in (Madgwick et al., 2011) which calculates the orientation information of the IMU using acceleration and velocity data. Measurements made with IMUs tend to drift over time, so in a second stage we compensate for the drift using absolute position information obtained from a Microsoft Kinect sensor. The fusion of sensor data also allows to compensate for faulty or missing measurements. We have carried out some initial experiments on arm tracking. The first results show that our technique for data fusion has the potential to be used to record common medical exercises for clinical movement analysis.

# 1 INTRODUCTION

A considerable amount of literature has been published on movement analysis using Inertial Measurement Units (IMUs) (Cloete and Scheffer, 2008; Jung et al., 2010; Rodriguez-Angeles et al., 2010). An IMU is a device that measures velocity, orientation, and gravitational forces, using a combination of accelerometers and gyroscopes, sometimes also magnetometers. IMUs can provide tracking data for robotic controls, gesture recognition and medical applications, such as joint angle determination or gait analysis. However, a persistent problem of IMU measurements, is that they tend to drift over time. Madgwick *et al.*(Madgwick et al., 2011) presented a filter to extract orientation information from IMU data. The benefit of this filter is that it reduces the drifting of the orientation information. The aim of this work is to fuse relative measurements obtained from an IMU, with absolute position measurements obtained from an optical system. We implement the data fusion using a Kalman filter, the fused data is then used inside a control loop and processed for enhanced tracking precision. The method proposed allows missing or faulty data from one of the two sources (IMU or Kinect) to be compensated for allowing for a stable system suitable for medical applications.

## 1.1 Optical Tracking

In recent years, optical based motion analysis has been increasingly used in medical applications (Claasen et al., 2011). Common optical systems record marker positions in order to extract patient motion information (Liguo et al., 2011). Other types of optical systems are based on arrays of cameras that provide 3D sensing. Since camera technology has become less expensive in the last decade, its use in medical motion analysis is very popular. Lately, 3D depth sensors have also become inexpensive and multi-sensor systems like the affordable Microsoft Kinect (includes an optical camera and a 3D depth sensor), are an attractive choice for carrying out medical motion detection and analysis. Optical motion analysis is used in various application fields such as joint angle derivation (Bo et al., 2011), evaluation of patient activity (Cordella et al., 2012), patient posture analysis (Obdrzalek et al., 2012; Xiao et al., 2012; Zeng et al., 2012), robotics (El-laithy et al., 2012) and gesture recognition (Patsadu et al., 2012).

## 1.2 IMU

Theoretically, speed of movement and distance can be determined by integration of the acceleration data


Kalkbrenner C., Hacker S., Algorri M. and Blechschmidt-Trapp R..
Motion Capturing with Inertial Measurement Units and Kinect - Tracking of Limb Movement using Optical and Orientation Information.
DOI: 10.5220/0004787601200126
In *Proceedings of the International Conference on Biomedical Electronics and Devices* (BIODEVICES-2014), pages 120-126
ISBN: 978-989-758-013-0

from an IMU. But since integration operates like a low pass filter, drifting errors occur. This effect is shown in (1).

$$\int cos(2\pi f t)\, dt = \frac{1}{2\pi f} sin(2\pi f t) \qquad (1)$$

As can be seen, the amplification term $(2\pi f)^{-1}$ is inversely proportional to frequency, so high frequencies fall off and low frequencies are amplified. As high frequency noise present in the IMU measurements is filtered, the offset in the measurements is amplified, which may cause drift.

The Madgwick filter (Madgwick et al., 2011) was proposed to calculate the spatial orientation in a computationally efficient, wearable inertial human motion tracking system used for rehabilitation applications. The algorithm is applicable to IMUs using tri-axis gyroscopes and tri-axis accelerometers. It uses a quaternion representation so that accelerometer and gyroscopic data can be used in an analytically derived and optimised gradient descent algorithm to compute the direction of the gyroscope measurement error as a quaternion derivative. With that, the orientation of the IMU relative to the earth frame can be determined.

Because of its low computational load and its ability to operate at a low sampling rate, the algorithm greatly reduces the hardware and power necessary for wearable, inertial movement tracking. In addition to this, the level of accuracy of the Madgwick filter exceeds that of most other approaches to determine the IMU orientation. IMUs are used because of their versatile capabilities and high precision. Research on IMUs is found in a wide range of fields such as joint angle estimation (Bo et al., 2011), pedestrian tracking (Fischer et al., 2012) and general motion analysis (Liguo et al., 2011; Taffoni et al., 2011; Zhang et al., 2011).

## 2 METHOD

The IMU developed by the University of Applied Sciences in Ulm is composed of a tri-axis gyroscope, a tri-axis accelerometer MPU-6000 (from *InvenSense*), a rechargeable battery and a Bluetooth gateway (Glaz, 2011) (Walter, 2012). The IMU delivers seven measurements per sample, three gyroscope values, three accelerometer values and the temperature. Each value is coded in two bytes, so the IMU transfers 14 bytes and two additional Start and Stop bytes to the computer at each sample step. The sampling rate can be configured from 60 Hz up to 300 Hz. In the present study a sampling rate of 100 Hz suffices.

The data delivered by the 3D depth sensor in the Microsoft Kinect is accessed using the Microsoft SDK. Data is accessed with a sampling rate of 30 Hz and the SDK is able to track the motion of up to four persons simultaneously. The SDK provides the tracking information of each person as 20 absolute 3D position coordinates of the joints shown in the skeleton model in Fig. 1.

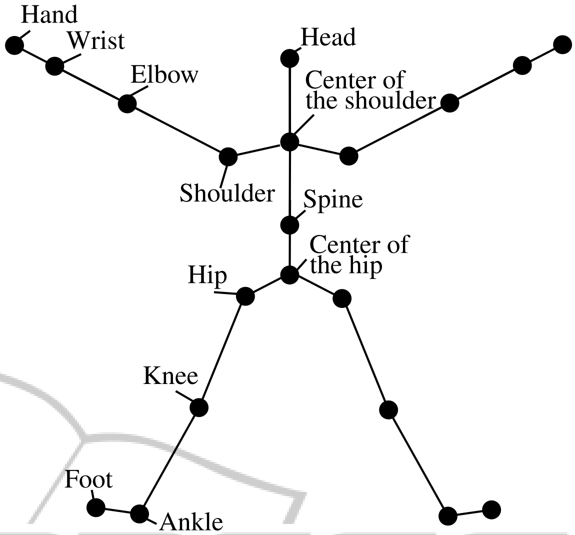


Figure 1: Joint positions described within the Skeleton-model offered by the Microsoft Kinect sensor.

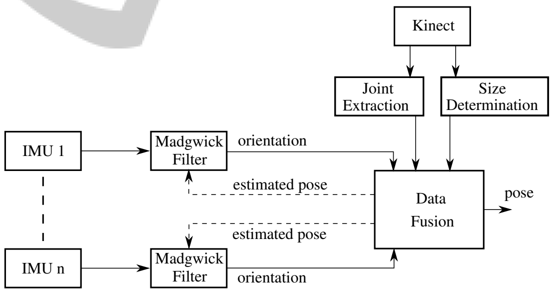


Figure 2: Flowchart of the data fusion algorithm.

Like most sensors, IMUs and the Kinect sensor are not immune to measurement artifacts. Besides the presence of drift, other events (such as rapid movements, occlusions, disturbance in the Bluetooth communication, optical or magnetic noise, etc.) can lead to faulty or missing measurement data from one of both sensors. In the present work we try to compensate for drift as well as missing or faulty data using an algorithm that fuses information from IMUs and the Kinect. To fuse the data we developed an algorithm (Fig. 2) that uses an embedded Kalman Filter. We explain the algorithm next.

We will explain the fusion algorithm using an example of tracking a human upper and lower arm (Fig. 3). For this example, the 3D joint positions of the elbow $P^I_{n1}$ and the wrist $P^I_{n2}$ are tracked using two IMUs

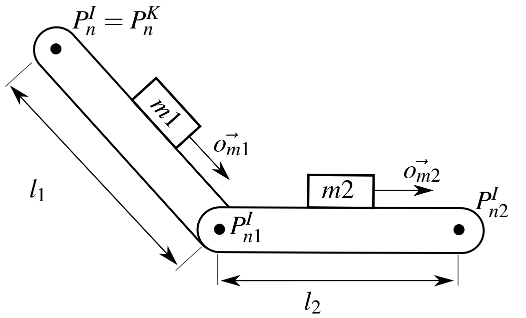


Figure 3: Derivation of joint positions $P_{n1}^I$ and $P_{n2}^I$ using two IMUs $m1$ and $m2$. The length $l1$ and $l2$ as well as the initial joint positions $P_n^K$ are provided by the Kinect.

$m1$ and $m2$. The initial shoulder coordinate $P_n^I$ is taken from the corresponding position coordinate $P_n^K$ acquired by the Kinect. Using the quaternion representation that results from processing the IMU data with the Madgwick filter, the vector $\vec{o}_m$, which describes the direction the front side of the IMU is looking at (commonly known in graphics as lookAt vector, see Fig. 3), can be determined. Based on the vector $\vec{o}_m$ and the known length of the upper arm $l_1$ and lower arm $l_2$ the joint positions can be determined. First the unit orientation vectors of the 2 IMUS $\vec{o}_{m1}$ and $\vec{o}_{m2}$ are multiplied by the length of the upper and lower arm.

$$\overrightarrow{p_{m1}} = \overrightarrow{o_{m1}} \cdot l_1, \qquad \overrightarrow{p_{m2}} = \overrightarrow{o_{m2}} \cdot l_2 \tag{2}$$

With the addition of the resulting vector $p_{m1}$ to the initial shoulder coordinate $P_n^I$, the position of the elbow joint $P_{n1}^I$ can be determined. The calculation of the wrist joint position $P_{n2}^I$ can then be determined by adding $p_{m2}$ to the now known elbow coordinate $P_{n1}^I$.

$$\overrightarrow{OP_{n1}^I} = \overrightarrow{OP_n^I} + \overrightarrow{p_{m1}}, \qquad \overrightarrow{OP_{n2}^I} = \overrightarrow{OP_{n1}^I} + \overrightarrow{p_{m2}} \tag{3}$$

The 3D coordinates of the elbow and wrist positions are used for the Kalman filter. In the next step the Kinect data is prepared. As mentioned before, the Kinect measures the absolute 3D coordinates of 20 joint positions of every tracked person. These joint positions are used inside the Kalman filter to adjust the correspondent joint positions obtained by the IMUs. The corrected, fused results of the Kalman filter are fed back to the Madgwick filter to compensate for existing orientations errors.

The Kalman filter is determined using basic knowledge from (Wendel, 2007), (Koehler, 2005) and (Jekeli, 2001). The fundamental equations unfold as follows:

$$x^-_{n/n1/n2/\ldots} = \begin{pmatrix} x_s \\ y_s \\ z_s \end{pmatrix} = A \cdot \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} + v \tag{4}$$

$$y_{n/n1/n2/\ldots} = \begin{pmatrix} x_m \\ y_m \\ z_m \end{pmatrix} = H \cdot \begin{pmatrix} x_k \\ y_k \\ z_k \end{pmatrix} + w \tag{5}$$

where (4) describes the system state $x^-_{n/n1/n2/\ldots}$ as the true position in space $(x_s, y_s, z_s)^T$ obtained by multiplying the parameter matrix $A$ with the coordinates $P^I_{n/n1/n2/\ldots} = (x_i, y_i, z_i)^T$ calculated in (3) and the correlated noise $v$. The measurement model (5) describes the vector of true position $y_{n/n1/n2/\ldots}$ in space $(x_m, y_m, z_m)^T$ obtained by multiplying the parameter matrix $H$ with the joint position data of the Kinect $P^K_{n/n1/n2/\ldots} = (x_k, y_k, z_k)^T$ and the correlated noise $w$. $A$ and $H$ are the usual parameter matrices of a Kalman filter. For our simple implementation, we used unit matrices for $A$ and $H$.

The Kalman-Gain $K$ is described in (6) where $P$ is the covariance of the IMU and $R$ is the covariance of the Kinect. For a detailed derivation see (Maybeck, 1982).

$$K = P \cdot H^T (H \cdot P \cdot H^T + R)^{-1} \tag{6}$$

As reference values for the covariances, we used values taken from the datasheets of the IMUs and the Kinect. After empirical studies, the basic values were set to $R = 0.015$m for the Kinect and to $P = 0.005$m for the IMU. The covariance $R$ of the Kinect is dynamic and changes depending on the tracking state of the Kinect and on the identified outliers in the calculated positions. The difference between the last calculated position and the next position received by the Kinect is described by $\Delta s$. For our applications, we established as maximum $\Delta s$ of 0.15m so that, if the distance between two consecutive measurements exceeded 0.15m, the covariance matrix $R$ was recalculated as follows:

$$R = \begin{pmatrix} R_x & 0 & 0 \\ 0 & R_y & 0 \\ 0 & 0 & R_z \end{pmatrix} + \begin{pmatrix} \Delta s_x^2 & 0 & 0 \\ 0 & \Delta s_y^2 & 0 \\ 0 & 0 & \Delta s_z^2 \end{pmatrix} * \mathcal{K} \tag{7}$$

where $\mathcal{K}$ is empirically set to 15 to obtain best results. Using the described dynamic covariance matrix $R$, the system behaves robustly in the presence of tracking errors produced by the Kinect (Nischwitz et al., 2007). For each joint $n/n1/n2/\ldots$ both IMU and Kinect positions are fused in (8) to get the new position $x^+$. Depending on the Kalman-Gain $K$ the data gets weighted differently in each step.

$$x^+ = x^- \cdot K \cdot (y - H \cdot x^-) \tag{8}$$

The resulting positions provided by the Kalman filter are then used to create a fused rotation matrix $M$ for each tracked limb. To create $M$ we need three vectors, $v_{front}$, $v_{up}$ and $v_{side}$, which respectively describe

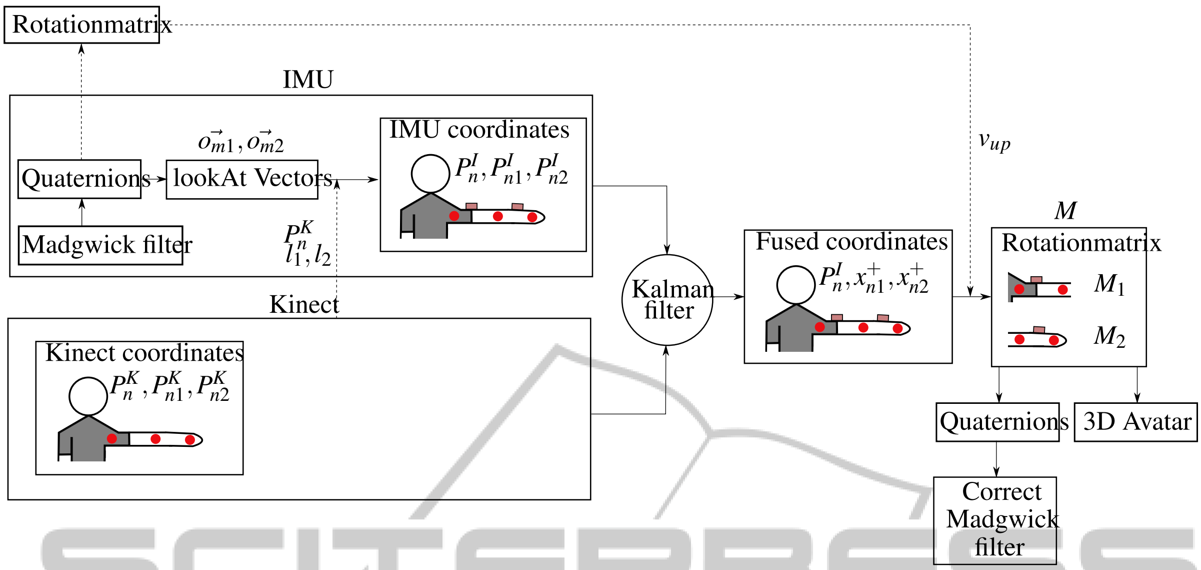


Figure 4: Flowchart of data types and their interactions between each other.



in what directions the front, up and lateral sides of the IMUs are looking at. The coordinates resulting from the Kalman filter are used to calculate the unit $v_{front}$ vector,

$$\vec{v}_{front} = \frac{\overrightarrow{P_n^I x_{n1}^+}}{\|\overrightarrow{P_n^I x_{n1}^+}\|} \tag{9}$$

The vector $v_{up}$ needed for the fused rotation matrix $M$ cannot be calculated only from the two joint positions, but can be extracted from the orientation Quaternions delivered by the Madgwick Filter. The Quaternion data from the Madgwick Filter is translated into a rotation matrix (in our case using Microsoft XNA or OpenGL) from which $v_{up}$ gets extracted. $\vec{v}_{side}$ can be calculated out of the cross product of $v_{front}$ and $v_{up}$ :

$$\vec{v}_{side} = \vec{v}_{front} \times \vec{v}_{up} \tag{10}$$

$$M = \begin{pmatrix} \vec{v}_{x,front} & \vec{v}_{x,side} & \vec{v}_{x,up} \\ \vec{v}_{y,front} & \vec{v}_{y,side} & \vec{v}_{y,up} \\ \vec{v}_{z,front} & \vec{v}_{z,side} & \vec{v}_{z,up} \end{pmatrix} \tag{11}$$

The fused rotation matrix $M$ is now used to correct the orientation results of the Madgwick Filter. To do so the fused rotation matrix $M$ gets converted back into a Quaternion (in our case using Microsoft XNA or OpenGL) and replaces the old orientation information of the Madgwick-Filter.
An overview of the whole process of converting the different data types and fusing them together can be seen in Fig. 4.

## 3 RESULTS

The first step of our evaluation consisted in carrying out a battery of tests to determine the accuracy of the proposed system. For these tests, the coordinates of the right elbow of 10 different test persons were measured while the test persons were not moving at all. For each test person a dataset of 1000 measured joint coordinates of the right elbow was recorded (10s at a measurement rate of 100Hz). The standard deviation of the resulting joint coordinates of the fusion algorithm compared to the real position was measured. The evaluation of the measurements provided us with an average standard deviation of $\pm 1.47$cm in the x-direction, $\pm 1.62$cm in the y-direction and $\pm 2.20$cm in the z-direction.
The second step of our evaluation consisted of tracking the movement of the arm. For this experiment, a patient periodically moved his/her tracked arm up and down as shown in Fig 5. A subset of the Kinect and IMU measurements of the right elbow position coordinates is shown in Fig 6 and Fig. 7. The Kinect was

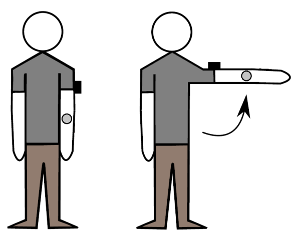

Figure 5: Reference exercise of the patient. The gray circle indicates the tracked elbow position. The black box is the sensor attached to patients arm.

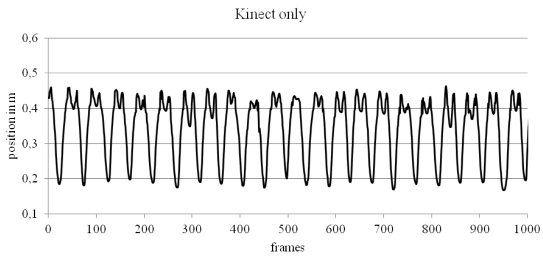


Figure 6: Tracked x-coordinates by the Kinect while the patient is moving his/her arm periodically up and down.

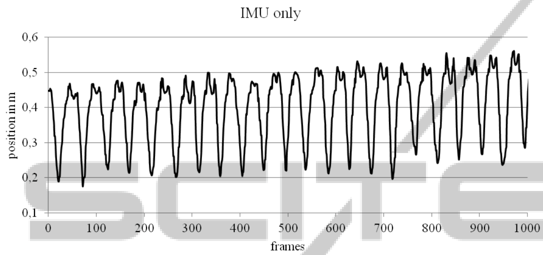


Figure 7: Tracked x-coordinates by the IMU while the patient is moving his/her arm periodically up and down.

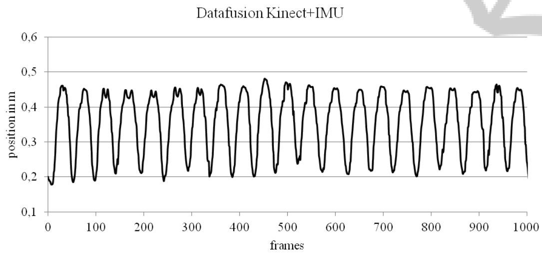


Figure 8: Resulting x-coordinates of the fusion algorithm while the patient is moving his/her arm periodically up and down.

able to track the elbow without any noticeable drift while the acquired data from the IMU shows some drift (0.1mm in 10 s). As shown in Fig. 8 the occurring drift while tracking the elbow movement is removed in the fused data.

Several problems appear when acquiring movement data with the Kinect sensor. The most common issue observed occurs whenever body parts of the tracked person are hidden from the sensor or are out of the range of sensing. If this happens, the algorithm provided by Microsoft marks appropriate joints with the state *not visible*. While in this state, joint positions cannot be recognized. During such a phase the fusion algorithm passes on the Kinect data and uses only IMU coordinates. From our experimental results we could establish that our IMU presented an average drift of approximately 0.01mm/s. From this measurement, and depending on the precision required by a

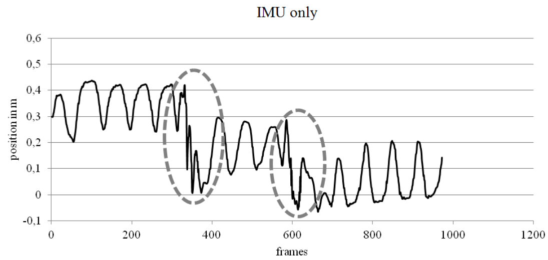


Figure 9: Tracked x-coordinates by the IMU while the patient is moving his/her arm periodically up and down. The abrupt movements that cause errors within the Madgwick-Filter are marked by gray dashed circles.

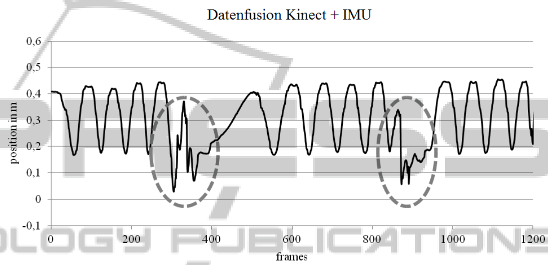


Figure 10: Resulting x-coordinates of the fusion algorithm while the patient is moving his/her arm periodically up and down. The abrupt movements that cause errors within the Madgwick-Filter are marked by gray dashed circles.

particular application, we can establish an experimental Kinect time-out window. That is, the maximum amount of time that we can pass on the Kinect measurements while still holding the IMU measurements stable. For example, if a precision of 1mm in the measurement of joint coordinates is required, we need to perform sensor data fusion at least every 100s.
The third step of our evaluation consisted again of tracking a periodic elbow movement, only this time the patient would occasionally move the arm fast and abruptly. Fig. 9 shows the x-coordinates of an IMU tracked elbow in this scenario. While periodically moving the arm, the patient introduces intentional errors by moving his/her arm way too fast for the IMU to track. These moments are marked by gray dashed circles. After the forced errors the patient continues his/her periodic movement normally. The fast movements cause the Madgwick filter to calculate a wrong orientation of the IMUs placed on the arm of the patient. Therefore the calculated position coordinates are incorrect. In Fig. 10 the same experimental results are shown after fusing the IMU data with the Kinect data. As can be seen, the orientation error of the IMU gets corrected within three to four cycles of movement after the error occurred. In a fourth step of our evaluation protocol, we tried to evaluate if the fusion algorithm could compensate for artifacts in the Kinect

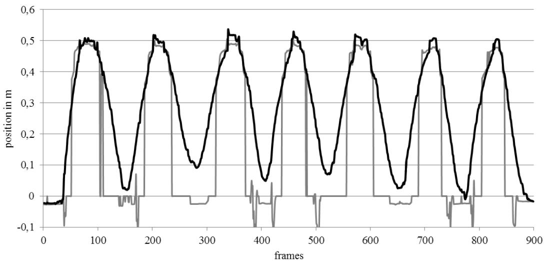


Figure 11: The black curve shows the resulting x-coordinates of the fusion algorithm while the vision of the Kinect is disturbed. The corresponding Kinect coordinates are shown in the gray curve. While this curve is at zero, the Kinect is not able to detect the joint and with that, it does not provide data for the fusion algorithm.

measurements. For this step, the same experiment of moving the arm periodically up and down was performed. Fig. 11 shows the x-coordinates of the wrist position obtained from the fusion algorithm in black and from the Kinect in gray. During this exercise the view of the Kinect was periodically obstructed on purpose. While the gray curve is on zero, the Kinect doesn't see the wrist and is not able to deliver any data to the fusion algorithm. As can be seen, missing Kinect data over a short time is compensated for using only IMU data. An important aspect to maintain the stability of the Kinect measurements even in the presence of periodic obstructions is the possibility to dynamically recalculate the covariance of the Kinect as shown in (7).

The last step in our evaluation protocol was a first, exploratory measurement done in a single Parkinson patient. We wanted to qualitatively assess if the high accuracy of the IMU measurements make them suitable to track very small movements such as tremor in Parkinson disease. The proposed system was in fact able to detect the Parkinson tremor without drift during a 10 minute experiment.

# 4 CONCLUSIONS

In this paper we propose a novel algorithm to carry out sensor data fusion. In particular, we fuse data obtained from IMUs and the Kinect while tracking limb movement. Our fusion algorithm uses the Madgwick filter as part of a control loop, a Kalman filter to fuse information and quaternion correction to maintain stability of the measurements. A battery of initial, exploratory experiments allowed us to assess that the fusion of data from the IMUs and the Kinect provide increased precision and stability for movement tracking. We could also assess that data fusion was able to correct errors in the measurements either by dropping faulty measurements or by relying only on one sensor when data from the second one was unavailable.

In (Obdrzalek et al., 2012) the accuracy of the Kinect sensor was examined. The authors wanted to determine if the Kinect meets the requirements for medical posture analysis. During their investigations, they observed a standard deviation of the joint coordinates measured by the Kinect of $\pm 5.5$cm. In our experiments with sensor data fusion we observed a standard deviation of the joint coordinate measurements of $\pm 2.20$cm, which, while encouraging, is still very low compared to high end optical tracking systems.

As part of the research carried out in (Jung et al., 2010) a system of IMUs was used for motion analysis. The IMUs were used to record and display postures and movements of the upper body. However, this was only possible with a limited mobility of the patient and an additional individual calibration of the IMUs. By comparison, the introduction of the Kinect sensor in our experiments allowed for higher flexibility in the movements without the need to recalibrate the IMUs for each patient.

To fully evaluate the capabilities of the proposed system in medical applications, we need to carry out additional studies on larger groups of patients, different locations and different types of movements. Further studies are also needed to better outline the limitations of the developed application and improve the overall system. A quantitative study using controlled movements in a robotic arm could be used to precisely quantify the precision of the tracking algorithm proposed. In future work we want to use the system to track multiple persons, record therapy processes and support clinical evaluation of diseases such as Parkinson.

# ACKNOWLEDGEMENTS

The authors would like to thank Karl Dubies and Michael Stuber for their assistance. This work was supported by a grant from the Ministry of Science, Research and the Arts of Baden-Wuerttemberg (Az: 33-7533-7-11.6-10/2).

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