Towards Human Motion Capturing using Gyroscopeless Orientation Estimation

Ulf Blanke
Computer Science, TU Darmstadt
blanke@cs.tu-darmstadt.de

Bernt Schiele
MPI Informatics, Saarbrücken
schiele@mpi-inf.mpg.de

Abstract

Current systems for motion capturing based on inertial measurement incorporate several powerhungry sensor modalities to accurately estimate the sensor's orientation. To drive motion capturing towards longterm applications, we use a reduced sensor setting based on accelerometers and magnetometers only to estimate orientation. We analyze this setting in real world conditions and provide results on initial experiments using a naturalistic dataset.

1. Introduction

Motion capturing (MoCap) has proven to be powerful for various areas, such as for the entertainment industry or recently for healthcare. For instance, MoCap is used to transfer human movements to virtual computer-generated characters or for gait analysis in the medical area. Also within activity recognition, MoCap is used to infer activities using body model-based action-primitives [1, 8].

Different techniques can capture human motion. Tracker-based approaches are widely used in the movie industry. Alternative systems use body-worn inertial measurement units (IMUs). Here, each limb is equipped with such a sensor. A set of sensor modalities – usually gyroscopes, accelerometers and magnetometers [6] – is fused to estimate full orientation of each limb in a global frame. While gyroscopes determine accurately angular changes, the other sensors keep this estimate drift free. Then a rigid body model is created using orientation of each limb.

Our goal is to make MoCap available for longterm recordings over days or even weeks. This imposes new requirements that prohibit deployment of existing systems due to high power consumption or long setup times. According to datasheets (see Table 1), a recent typical gyroscope draws about 5-10 times more power than magnetometers and acceleration sensors together.

While there exist several attempts to use power efficient accelerometers only [2, 7], results remain unsatisfying as stated in [4]. Others try to omit gyroscopes and yield promising results [5]. However, performance is reported on short term and artificial data for one sensor only. As we are specifically interested in human MoCap during daily activities, we use a similar approach to [5] and show its effectiveness by analyzing its accuracy in a naturalistic setting.

2. Orientation Estimation of Limbs

In order to empower MoCap for longterm usage, we ask the following question: *Using a reduced sensor setting, can we still perform accurate motion capturing of natural human movement?* We implement a model using magnetometers and accelerometers only. By estimation of magnetic north $\mathbf{n}$ and the gravity vector $\mathbf{g}$, we can define a coordinate system by simply obtaining a third axis by cross product. Note here that sensor measurements are errorprone to magnetic disturbance and motion, effecting the estimation of $\mathbf{g}$ and $\mathbf{n}$. To estimate a sensor's full orientation, we propose an algorithm based on a linear Kalman filter. Given a sequence of 3D-acceleration and 3D-magnetometer readings $\mathbf{a}$ and $\mathbf{m}$, we first use a sliding average window as lowpass filter. We then perform steps similar to [5] and [3] :

We feed $\mathbf{m}_{1\times 3}$ and $\mathbf{a}_{1\times 3}$ as measurement vector $\mathbf{z}_{1\times 6} = [\mathbf{m}; \mathbf{a}]$ into a Kalman filter. The Kalman filter is then parametrized by state covariance Q and measurement covariance R:

$$Q = 0.2 \cdot I_{6\times 6} \text{ and } R = \begin{bmatrix} \delta I_{3\times 3} & 0 \\ 0 & \gamma I_{3\times 3} \end{bmatrix}$$

where δ and γ define an adaptive filter by

$$\delta = |\parallel \mathbf{m} \parallel -1| \text{ and } \gamma = |\parallel \mathbf{a} \parallel -g|$$

and where g corresponds to gravity force $9.81 m/s^2$. Intuitively, δ increases when motion is present. Analogously, δ increases when magnetic disturbance is present (e.g., by metallic objects). As output of the Kalman filter, we gain smoothened and normalized magnetometer and accelerometer values $\mathbf{s} = [\mathbf{s}_a; \mathbf{s}_m]$. The Kalman filter is used for smoothing the input signal according to disturbances only. Therefore transformation matrix H equals identity $I_{6\times 6}$. Finally, we apply a simple algorithm to obtain full orientation represented by rotation matrix T:

$$\mathbf{r}_y = \mathbf{s}_m \times \mathbf{s}_a, \;\; \mathbf{r}_z = \mathbf{s}_a \text{ and } \mathbf{r}_x = \mathbf{r}_z \times \mathbf{r}_y$$

$$T = [\mathbf{r}_x, \mathbf{r}_y, \mathbf{r}_z]$$

Note that the second crossproduct for $\mathbf{r}_x$ removes the magnetic inclination, which corresponds to the angle between a magnetic reading and the horizontal groundplane.

Sensor	Gyroscope	Magnetometer	Accelerometer
Manufactor	LYPR540AH	HMC5843	ADXL330
Size in mm	4.4×7.5×1.1	4×4×1.3	4×4×0.35
Current in mA	10.8	2.0 at 50Hz, 1.0 at 20Hz	0.3

Table 1. Typical power consumption and form factors from datasheets.

3. Experiments

To analyze our approach we specifically choose a publicly available dataset containing substantial upper body motion [1]. We focus on a naturalistic workshop scenario, where 10 people perform a construction task, containing several hours of activities such as *drilling, sawing, screwing* and also *grabbing tools, fixing objects to the desk*, etc.

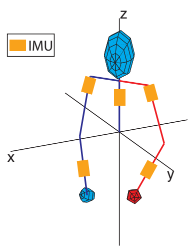

Figure 1. Estimated 3D model from 5 IMU sensors

We compare our approach to a commercially available solution incorporating a full sensor setting as in [6]. Five Xsens inertial measurement sensors were placed at the upper body. Fig. 1 shows the estimation of a bodymodel using Xsens sensors. Both the orientation estimate (denoted by rotation matrix T_{xsens}) and raw sensor values of the magnetometer and accelerometer at a sampling frequency of 50Hz were recorded. Upon raw sensor values we estimate the orientation using our approach (denoted by rotation matrix T). We provide two error measurements in order to evaluate our approach. First, we calculate the deviation angle between T and T_{xsens} for each reading at time t. We calculate mean and standard deviation for the sequence of readings across all subjects. Second, we calculate the average correlation between both orientation estimates over time.

Results. Fig. 2(a) shows the correlation between the orientation estimate of Xsens and our approach. Correlation of both orientation estimates is highest at the sensor mounted at the back (95%) and lowest at the right lower hand with 81%. While substantial amount of movement is present in the signal, overall correlation still remains high. Fig. 2(b) shows results in terms of angle deviation. Expectedly, deviation is lowest for the back mounted sensor (7°). Here, only moderate motion effects our orientation estimate. While motion increases along the kinematic chain (upper arm, lower arm) the deviation error increases also (up to 27°). We observed that most of the deviation occurs in posture changes, whereas steady moments contain almost no deviation. Additionally, the delay of our fusion approach adds to the mean error, especially during sudden movements. As a result the standard deviation increases towards the end of the kinematic chain. Interestingly, deviation for the left side is smaller than for the right side. All subjects are right-handed, resulting in less motion at the left arm. Also, electric machines (e.g., drilling machines), mainly held in the right hand, introduce magnetic disturbances increasing the deviation.

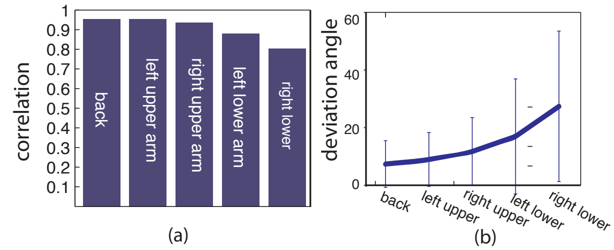

Figure 2. Error of orientation estimate

4. Conclusion and Future Work

Surprisingly good results can be achieved using acceleration and magnetometer sensors only for orientation estimation influenced by *natural* human motion. We experienced the highest deviation error of 27° to a commercially available sensor at the right lower wrist. Motion has a vast effect on the orientation estimate. We also conducted some initial experiments on daily activities (such as eating or working) that show lower deviation. Motion of the upper body occurs far less than in a construction scenario, suggesting generally better performance when used in everyday life.

Our findings indicate that using magnetometers and accelerometers only is suited to estimate the orientation of limbs and promising to perform MoCap. Equally important, requirements of a smaller form factor and a longer battery runtime to enable longterm recordings can be met. We are currently implementing such a sensor type to allow for longterm MoCap of daily activities.

References

[1] U. Blanke, B. Schiele, M. Kreil, P. Lukowicz, B. Sick, and T. Gruber. All for one or one for all? – Combining Heterogeneous Features for Activity Spotting. In *Comorea2010*.
[2] J. Chen, S. Lee, and D. DeBra. Gyroscope free strapdown inertial measurement unit by six linear accelerometers. *Journal of Guidance, Control, and Dynamics*, 17(2):286–290, 1994.
[3] A. Gallagher, Y. Matsuoka, and W. Ang. An efficient real-time human posture tracking algorithm using low-cost inertial and magnetic sensors. In *IROS2004*.
[4] D. Giansanti, V. Macellari, G. Maccioni, and A. Cappozzo. Is it feasible to reconstruct body segment 3-D position and orientation using accelerometric data? *IEEE TBE2003*.
[5] B. Huyghe, J. Doutreloigne, and J. Vanfleteren. 3d orientation tracking based on unscented kalman filtering of accelerometer and magnetometer data. In *SAS09*.
[6] H. Luinge. *Inertial Sensing of Human Movement*. PhD thesis, Twente University Press, 2002.
[7] D. Mizell and I. Cray. Using gravity to estimate accelerometer orientation. In *ISWC03*.
[8] A. Zinnen, C. Wojek, and B. Schiele. Multi activity recognition based on bodymodel-derived primitives. In *LoCa09*.