Gated Sensor Fusion: A way to Improve the Precision of Ambulatory Human Body Motion Estimation

KES Innovation in Medicine and Healthcare InMed-14

July 9, 2014

Alberto Olivares[1] Juan Manuel Górriz[1] Javier Ramírez[1] Gonzalo Olivares[2]

[1]Dept. of Signal Theory, Networking and Communications, Universidad de Granada, Spain

[2]Detp. of Computer Architecture and Computer Technology, Universidad de Granada, Spain

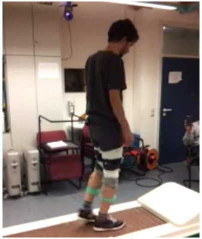
ugr Universidad de Granada

Outline

Introduction

Measuring human motion in medical practice

- Helps physicians to assess patients:
  - With neurodegenerative diseases.
  - Following rehabilitation processes.
  - In risk of falling.
  - With gait disorders.
  - With sleep disorders.
  - Suffering unnoticed nocturnal epileptic seizures.



Introduction

Human motion can be measured in different ways

- Camera-based systems
  - Cameras acting as observers.
  - Very accurate.
  - Reduced flexibility.
  - Reduced range (non ambulatory).
  - Expensive.
  - Privacy issues.
  - Examples: *Vicon*,*Qualisys*.
- Inertial systems
  - Inertial sensors in IMUs.
  - Lower accuracy.
  - High flexibility.
  - Ambulatory.
  - Non-expensive.
  - No privacy issues.
  - Examples: *Xsens*, *Shimmer*.

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.

Introduction

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.

Introduction

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.
- Observation: orientation estimation using accelerometer.

Introduction

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.
- Observation: orientation estimation using accelerometer.
- Observation only reliable when motion intensity is low.

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.
- Observation: orientation estimation using accelerometer.
- Observation only reliable when motion intensity is low.
- High motion intensity $\rightarrow$ High linear acceleration.

Introduction

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.
- Observation: orientation estimation using accelerometer.
- Observation only reliable when motion intensity is low.
- High motion intensity $\rightarrow$ High linear acceleration.
- Non satisfactory precision under changing motion conditions.

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.
- Observation: orientation estimation using accelerometer.
- Observation only reliable when motion intensity is low.
- High motion intensity $\rightarrow$ High linear acceleration.
- Non satisfactory precision under changing motion conditions.
- Optimal value of parameters different for low and high intensity.

Introduction

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.
- Observation: orientation estimation using accelerometer.
- Observation only reliable when motion intensity is low.
- High motion intensity $\rightarrow$ High linear acceleration.
- Non satisfactory precision under changing motion conditions.
- Optimal value of parameters different for low and high intensity.

We propose

- Dynamical modification of static parameters.

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.
- Observation: orientation estimation using accelerometer.
- Observation only reliable when motion intensity is low.
- High motion intensity $\rightarrow$ High linear acceleration.
- Non satisfactory precision under changing motion conditions.
- Optimal value of parameters different for low and high intensity.

We propose

- Dynamical modification of static parameters.
- Optimal values are switched according to detected motion intensity.

Introduction

Orientation estimation algorithms have constant parameters

- Kalman filters performance highly dependent on constant parameters.
- Parameters control confidence balance between estimation and observation.
- Observation: orientation estimation using accelerometer.
- Observation only reliable when motion intensity is low.
- High motion intensity $\rightarrow$ High linear acceleration.
- Non satisfactory precision under changing motion conditions.
- Optimal value of parameters different for low and high intensity.

We propose

- Dynamical modification of static parameters.
- Optimal values are switched according to detected motion intensity.
- Intensity is detected using spectrum analysis of acceleration signals.

Developed in the 70s for space missions

- To determine orientation of the spaceship.
- Examples: TRIAD and QUEST.
  - Orientation of two vector observations with respect to two vector references.
  - Vector observations: Magnetic field and acceleration in body frame.
  - Vector references: Local Gravity and Earth magnetic field vectors.
  - Only acceleration and magnetic field.
  - Output: orientation quaternion.

Recent approaches

- Fuse estimated quaternion with angular velocity orientation quaternion.
- Estimate orientation quaternion in different ways.
- Many variations have been proposed ALL with permanent tunning parameters.

We need to estimate motion intensity

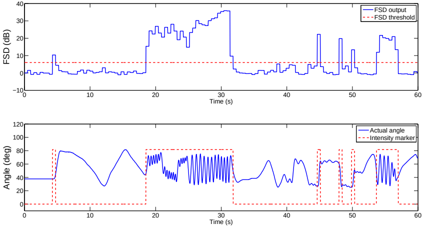
- There are many possibilities.
- Time analysis of acceleration and/or angular velocity.
  - Magnitude.
  - Variance.
- Frequency analysis of acceleration and/or angular velocity.
  - Framed Spectrum.
  - Long Term Spectral Envelope.
  - Estimation of PSDs.
- Output is compared to a predefined threshold to create a binary marker.
- Binary marker: 1 (high intensity), 0 (low intensity).

In this work we used

- The Framed Spectrum Detector $\rightarrow$ computationally efficient and accurate.
- Input $\rightarrow$ Acceleration magnitude.
- Output:

$$V(\mathbf{n}) = 10\log_{10}\left(\frac{1}{N_{FFT}}\sum_{l=0}^{N_{FFT}-1}\frac{X^2(l,n)}{N^2(l)}\right)$$

- N_{FFT} resolution of the FFT.
- $N(l)$: Average noise spectrum magnitude for the l band.
- $X(l,n)$ spectrum of input signal for the l band at frame n.



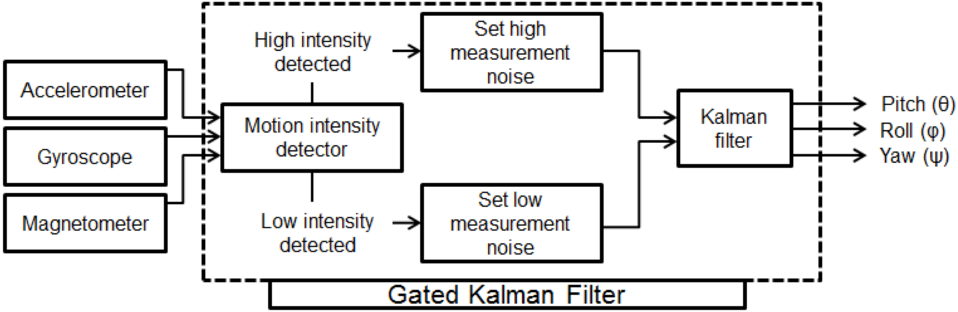
Most orientation estimation algorithms are based on the Kalman filter

- Kalman filter fuses accelerometer, gyroscope and magnetometer data.
- Fusion is strictly necessary.
- No sensor provides accurate estimates if used individually.
  - *Accelerometer* $\rightarrow$ Decomposition of Earth's gravity vector. Only valid if motion is very smooth.
  - *Gyroscope* $\rightarrow$ Integration of angular rate. Shows large drift.
  - *Magnetometer* $\rightarrow$ Decomposition of Earth's magnetic field vector. Only valid in magnetically clean environments.

As said before, Kalman filters have constant parameters

- Constant covariance matrix of process noise (Q).
- Constant covariance matrix of measurement noise (R).
- We will set 2 different values (intense motion and low motion).
- The values are changed accordingly (Gating).

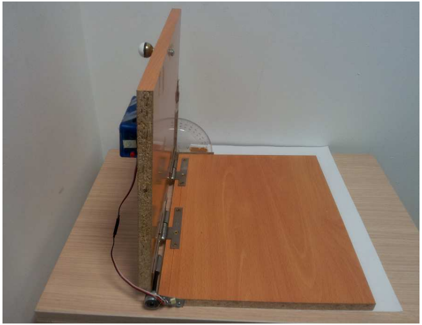
Structure of the Gated Kalman Filter

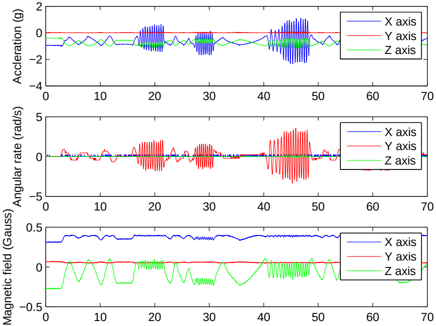


- High intensity $\rightarrow$ high linear acceleration $\rightarrow$ high variance of measurement noise.
- Low intensity $\rightarrow$ low linear acceleration $\rightarrow$ low variance of measurement noise.

Datasets

- 16 datasets of inertial and magnetic signals.
  - 3D acceleration, 3D angular rate and 3D magnetic field.
- MIMU: Wagyromag.
- Mechanical device to determine angle reference (ground truth).
- Each dataset contains both smooth and intense random motion.





Algorithms

- 4 orientation estimation algorithms.
  - 2 Kalman Filters: QUEST + gyro and gravity decomposition + gyro.
  - 2 Extended Kalman Filters: QUEST + gyro and gravity decomposition + gyro.

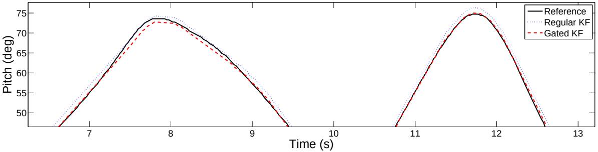
Experiment Workflow

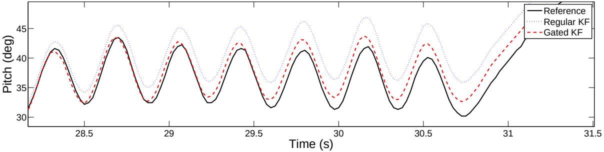
We have used a Monte Carlo procedure:

1. Load dataset and calibrate signals.
2. Initialize parameters.
3. Estimate orientation using all 4 algorithms.
4. Apply Adaptive Nelder-Mead Simplex Algorithm to minimize RMSE. Optimal parameters are found.
5. End of loop $\rightarrow$ average RMSE and optimal parameters for each algorithm.

Table: RMSE of estimated pitch angle with respect to the ground truth. Non-gated vs. gated algorithms. Last row shows the percentage of improvement by using the gated approach.

	KF	KF (QUEST)	EKF	EKF (QUEST)
RMSE (deg)	3.00 ± 0.72	1.50 ± 0.22	3.07 ± 1.13	2.26 ± 0.48
	G-KF	**G-KF (QUEST)**	**G-EKF**	**G-EKF (QUEST)**
RMSE (deg)	2.09 ± 0.56	1.48 ± 1.88	2.35 ± 0.97	2.24 ± 0.47
Improvement (%)	$\mathbf{29.34 \pm 12.03}$	0.89 ± 5.19	$\mathbf{23.31 \pm 10.70}$	0.93 ± 1.77





Discussion of Results

Effect of Covariance matrices

- Prediction equations:

$$\mathbf{x}_k^- = \Phi \mathbf{x}_{k-1}$$
$$P_k^- = \Phi P_{k-1} \Phi^T + Q$$

- Update equations:

$$K_k = \frac{P_k^- H^T}{H P_k^- H^T + R}$$
$$\mathbf{x}_k = \mathbf{x}_k^- + K_k (z_k - H \mathbf{x}_k^-)$$
$$P_k = (I - K_k H) P_k^-$$

- Φ: state transition matrix.
- $\mathbf{x}_k^-$: a priori state estimate.
- P_k^-: a priori system covariance matrix.
- Q: process noise covariance matrix.
- R: observation noise covariance matrix.
- K_k: Kalman filter gain.
- $\mathbf{x}_k$: a posteriori state estimate.
- P_k: a posteriori system covariance matrix.

Conclusions and Future Work

Conclusions

- Novel approach to improve precision of determination human body orientation.
- Applying a gating strategy to Kalman filter.
- Gating changes formerly permanent parameters according to motion intensity.
- Motion intensity is detected analyzing spectrum of acceleration magnitude.
- Experiments show improvement of up to 29% over non-gated approach.

Future work

- Multi-level variation (instead of 2 intensity levels).
- Fuzzy variation of parameters.

Thank you for your attention!

ugr Universidad de Granada