

# Magnetometer-Free IMU (Inertial Measurement Unit) Sensor Fusion For Wearable Motion Capturing Technology

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## Introduction

There are several applications for wearable motion capturing systems in sports, entertainment and medicine. Miniature IMU sensors can be used to capture relative motion without the aid of external peripherals. The size and power requirements of MEMS sensors make them a perfect candidate for incorporating into Wearable Technology.

In collaboration with the ARCCS (Accessible Routes for Crowdsources Cloud Services) group led by S. Hailes and C. Holloway [1], MEMS sensors are being developed to meet the requirements of several motion capturing projects. The goal of this project is to create a bodysuit capable of monitoring full human motion, transferring this motion to the cloud for post processing.

Such a system would have many applications including: monitoring outpatients for physiotherapists/therapists, and over the cloud teaching/assessing of athletes or performers such as dancers.

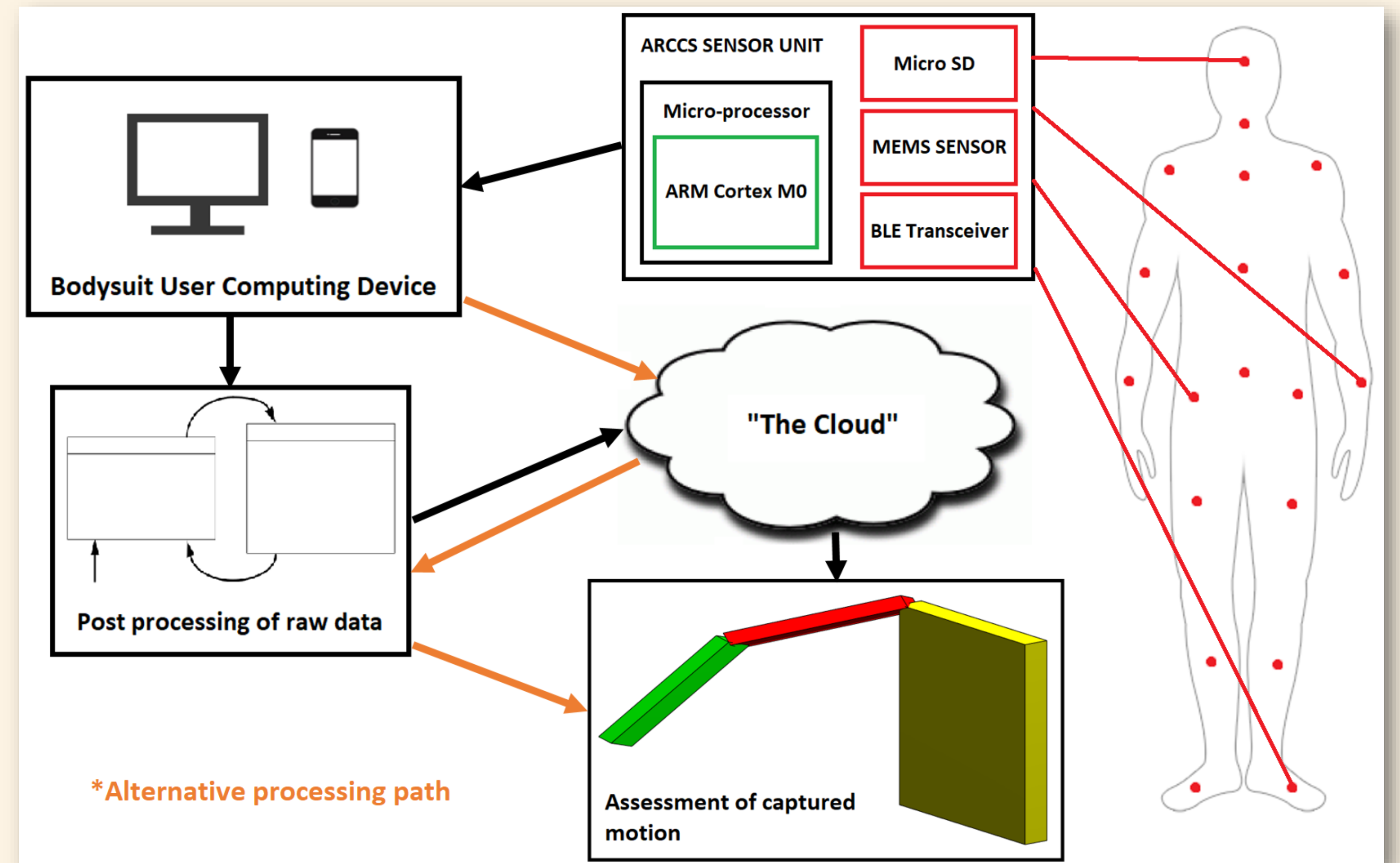


Figure 2: System flow diagram of the IMU motion capturing bodysuit

## Digital Filters

### Bayes' Theorem

Describes the probability of a state, based on prior knowledge of the system that relates back to the state of the system, or mathematically:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Where  $A$  and  $B$  are possible states.

- $P(A)$  is the probability of state  $A$  occurring regarding nothing else in the system.
- $P(A|B)$  is the probability of state  $A$  to occur given that  $B$  has happened.

### Kalman Filter

An algorithm which uses Bayesian interference to combine multiple estimated states to equate a statistically more probable estimation. The filter assumes the system is linear and the noise within is zero mean Gaussian distributed. The algorithm can be split into two parts, predict and correct.

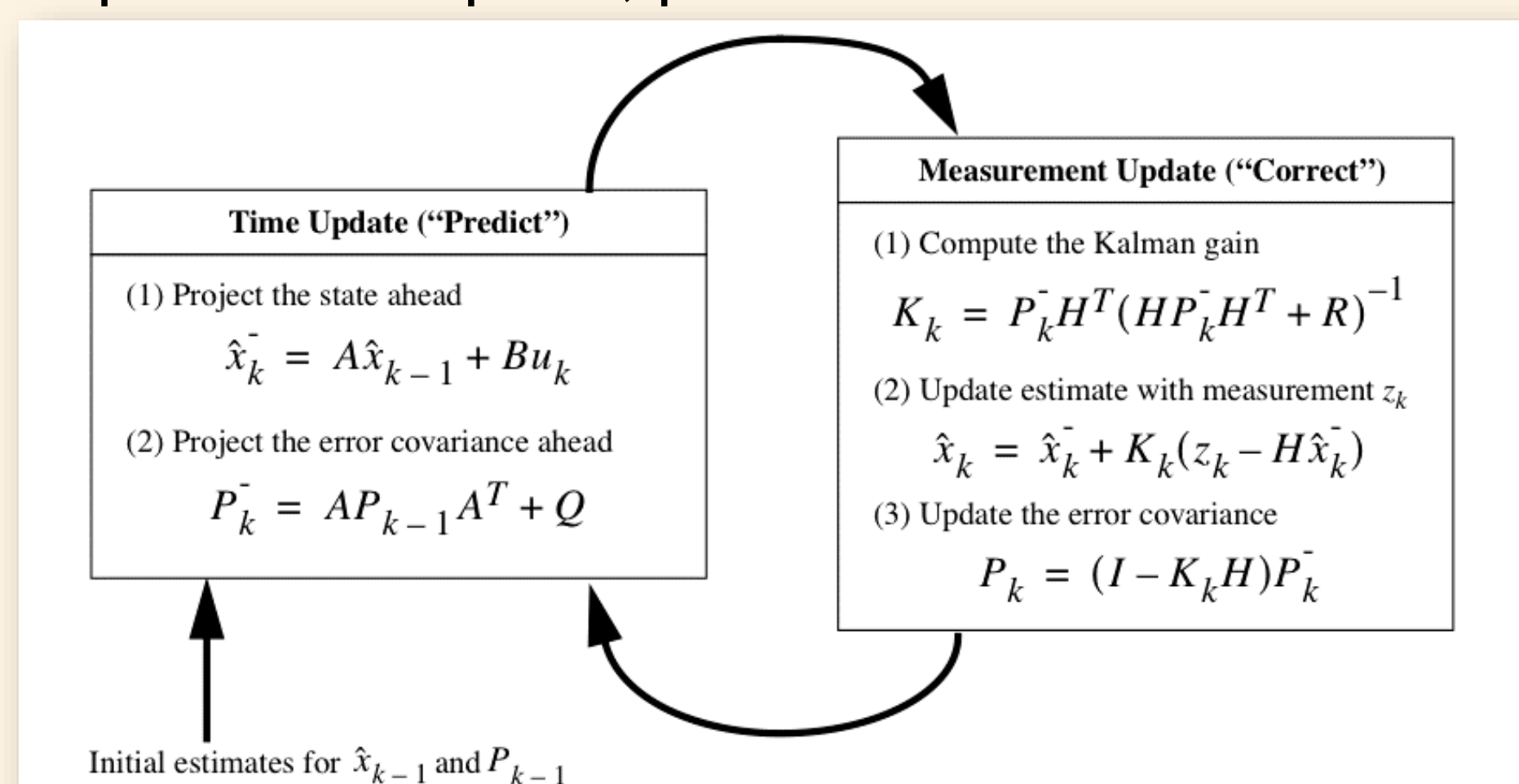


Figure 1: Flow of the Kalman Filter algorithm

### Extended Kalman Filter (EKF)

The nonlinear version of the Kalman Filter, the EKF linearizes the state estimation and covariance before applying a similar algorithm as the standard Kalman Filter. The main differences being:

1. The transition and observation models no longer need to be linear, however must be differentiable.
2. The state transition and observation matrices are the following Jacobians:

$$A_k = \left. \frac{\delta a}{\delta x} \right|_{\hat{x}_k, u_k}, \quad H_k = \left. \frac{\delta h}{\delta x} \right|_{\hat{x}_k}$$

### Unscented Kalman Filter (UKF)

Used when the transition and observation models are highly non-linear, the Unscented Kalman Filter uses the unscented transform technique to select a minimal set of points arounds the estimate. These points are then propagated through the nonlinear function to update the estimation and covariance of the estimate. The UKF can be relatively computationally costly compared with the EKF, however does not require the transition and observation models to be differentiable and removes the requirement of calculating the two Jacobians

## Orientation Calculation

During post processing, the roll, pitch and yaw of each sensor is calculated and plotted using spherical coordinates with prior knowledge of sensor locations.

From accelerometer data:

$$pitch = \arctan\left(\frac{Acc_y}{\sqrt{Acc_x^2 + Acc_z^2}}\right), \quad roll = \arctan\left(\frac{-Acc_x}{Acc_z}\right)$$

From gyroscope data:

$$\Delta pitch = \int Gyro_x dt, \quad \Delta roll = \int Gyro_y dt, \quad \Delta yaw = \int Gyro_z dt$$

## Results

To compare the results of the digital filter an ARCCS sensor was mounted on the end of a pendulum. Figure 3 shows the accelerometer's Y axis raw data as well the results after applying the three filters discussed.

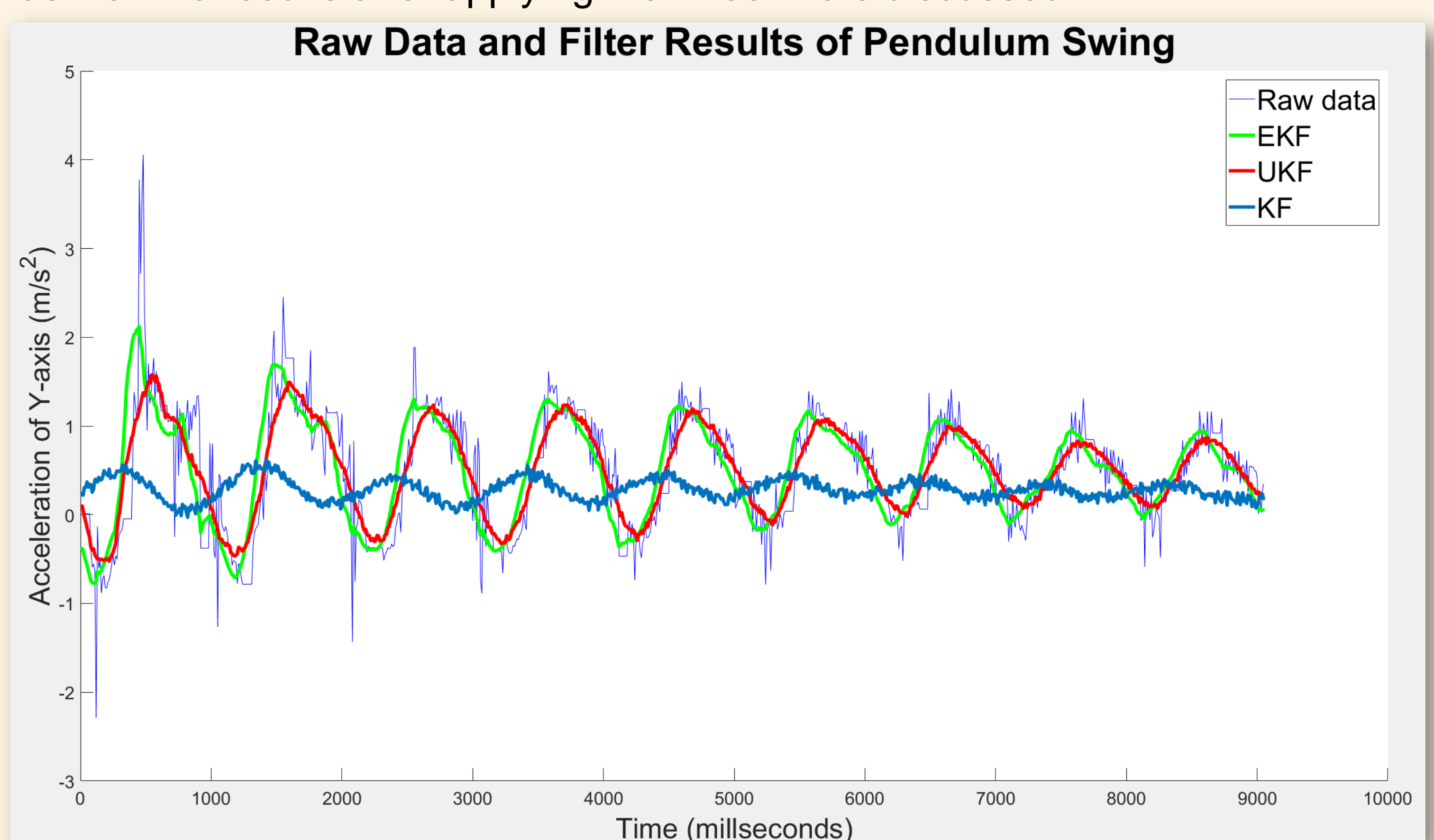


Figure 3: Accelerometer data and filtering results from ARCCS sensor mounted on a pendulum

## Conclusion

From the results collected at this point it is unclear which of the nonlinear filters have achieved a higher standard of filtering, however it is clear that the Kalman Filter is not capable of filtering even basic nonlinear functions.

The current demo (as seen by the accompanying video) allows the user to visually compare: the motion made with a 3D model, as well as the raw data with the filtered data. This allows qualitative assessment of the post processing procedure. A gold standard test processor must be determined to give a quantitative assessment.

