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MÜNSTER UNIVERSITY OF APPLIED SCIENCES
Department of Electrical Engineering and Computer Science

Bachelor Thesis

KALMAN FILTERING APPLIED TO ORIENTATION ESTIMATION IN HUMAN BODY MOTION ANALYSIS

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*A thesis submitted in partial fulfilment of the requirements for the degree
of Bachelor of Science in Electrical Engineering*

March 2015

Statement of Authorship

I hereby certify that this bachelor thesis has been composed by myself, and describes my own work, unless otherwise acknowledged in the text. All references and verbatim extracts have been quoted, and all sources of information have been specifically acknowledged. It has not been accepted in any previous application for a degree.

Granada, 27th March 2015

Robin Weiß

Preface

This thesis was submitted in partial fulfilment of the requirements for the degree of Bachelor of Science in Electrical Engineering. It describes the implementation of a new Kalman filter based orientation algorithm to improve the estimation of orientation angles by means of inertial sensors.

I took part in the joint research project “Human Body Motion Analysis of Patients with Neurodegenerative Diseases by Means of Inertial Sensors” between the Research Centre for Information and Communications Technologies of the University of Granada (CITIC-UGR), Spain, and the Department of Neurology of the Klinikum Großhadern, which is part of the Ludwig Maximilian University of Munich, Germany. The goal of the overall project was to obtain several gait parameters by wearable inertial sensors and validate them against conventional methods such as force plates and cameras in combination with visual markers. Physicians and medical researchers are interested in this approach of body motion analysis, as it can assist the diagnosis of neurodegenerative diseases such as Parkinson’s. Prior to this thesis I completed a three-months internship at the CITIC-UGR in which I worked on the synchronisation of a force measuring plate and inertial sensors within the above-mentioned project.

MÜNSTER UNIVERSITY OF APPLIED SCIENCES
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ABSTRACT

Kalman Filtering Applied to Orientation Estimation in Human Body Motion Analysis

by Robin Weiß

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Abbreviations

CITIC-UGR	Research Centre for Information and Communications Technologies of the University of Granada
IMU	Inertial measurement unit
MARG sensors	Magnetic, angular rate, and gravity sensors
MEMS	Microelectromechanical systems
MIMU	Magnetic inertial measurement unit

Notation

- a** Three-dimensional acceleration vector
- B** Control matrix that relates the control input to the state \mathbf{x}
- d Desired filter response of a linear discrete-time filter
- e Error signal of a linear discrete-time filter
- F** Three-dimensional force vector
- H** Measurement sensitivity matrix defining the linear relationship between the state of the dynamical system and the measurements that can be made
- k Discrete time normalised to sampling interval (sample number, $k \in \mathbb{N}^0$)
- K Weighting factor
- K** Kalman gain matrix
- m Mass
- n Discrete time
- P** Covariance matrix of state estimation uncertainty

Φ	State transition matrix of a discrete linear dynamical system
Q	Covariance matrix of process noise in the system state dynamics
R	Covariance matrix of observational (measurement) uncertainty
μ	Mean value of conditional probability density
σ^2	Variance
σ	Standard deviation
t	Continuous time
u	Nominal velocity
\mathbf{v}	Measurement noise vector
w	Noise term
w_0, w_1, w_2, \dots	Impulse response of a linear discrete-time filter
\mathbf{w}	Process noise vector
x	One-dimensional location
\hat{x}	Estimate of x
\mathbf{x}	State vector of a linear dynamical system
\mathbf{x}_k	The k th element of a sequence $\dots, \mathbf{x}_{k-1}, \mathbf{x}_k, \mathbf{x}_{k+1}, \dots$ of vectors
$\hat{\mathbf{x}}$	Estimate of the state vector of a linear dynamical system
$\hat{\mathbf{x}}_k^-$	A priori estimate of $\hat{\mathbf{x}}$, conditioned on all prior measurements except the one at time t_k
\mathbf{y}	Observation vector of a dynamical system
$y(0), y(1), y(2), \dots$	Time series that serves as input to a linear discrete-time filter

z^{-1} Unit-delay
 \mathbf{z} Vector of measured values

Introduction

1.1 General

Orientation estimation assisted by inertial sensors have become an integral part of medical diagnosis and therapy techniques as it provides an objective means of monitoring and assessing human body motion.

1.2 Motivation

1.3 Goals

The goal of this thesis was implementing a new Kalman filter based orientation algorithm proposed by Bennett et al. in [5] to improve the estimation of orientation angles by means of inertial sensors. The filter algorithm should be implemented using MATLAB[®] and validated against existing algorithms by comparing their respective error rates. An existing system for human body motion analysis called GaitWatch was available so that no new hardware had to be developed to gather the movement data.

1.4 Methodology

Subsequent to the introductory overview of the subject and the definition of the project objectives, this chapter ends with a description of the state of the art. Chapter 2 outlines the fundamentals of MARG sensors and

gives a detailed description of the GaitWatch device. Chapter 3 explains the theoretical basics of digital filters including the Kalman filter as a particular one. Those are necessary for the actual implementation of the filter and the orientation estimation in Chapter 4, in which also the results are presented and discussed. Finally, Chapter 5 concludes and proposes possible future work.

As additional means to communicate with my supervisor and enable him to follow the progress of the project at any time we used Pivotal Tracker, a tool for agile project management and GitHub, a repository hosting service based on the distributed version control system Git. This thesis is written in the document markup language \LaTeX .

1.5 State of the Art

MARG sensors can be found in smart phones, fitness trackers, and other wearable devices where they have become a prevalent research environment for estimation and tracking of human body motion [5]. They are used in activity monitoring [6][7][8], rehabilitation [9][10], sports training [11][8], and localisation [12][13]. Moreover they have numerous applications in navigation.

There are several research works in the literature dealing with orientation estimation by means of inertial sensors. The state of the art at the commencement of the project is described below. Subsequently, current attempts to revolutionise medical research assisted by inertial sensors are presented.

1.5.1 Kalman Filtering in Orientation Estimation

Given the fact that inertial sensors are used to establish objective body motion parameters that affect medical diagnosis, therapy, and rehabilitation, the need of a high level of accuracy becomes obvious. A wide variety of Kalman filter algorithms have been developed in the literature.

1.5.2 MARG Sensors in Medical Research

In March 2015, Apple Inc. announced an open source framework called ResearchKit [14] that, amongst others, takes advantage of the MARG sensors in the iPhone to track movement of patients in daily life. Thus

medical researchers obtain robust data with far more regularity than it was possible when patients complete tasks at hospitals or other research facilities in irregularly intervals. Moreover, according to Apple Inc. ResearchKit simplifies recruiting participants from all over the world which results in a more varied study group that provides a more useful representation of the population.

In August 2014, the Michael J. Fox Foundation for Parkinson's Research and Intel Corporation [15] announced a collaborative research study on objective measurement of Parkinson symptoms. They aim to collect movement data of thousands of patients twenty-four seven at over 300 samples per second by means of unobtrusive wearable devices and store them on a big data analytics platform. The data platform, deployed on a cloud infrastructure, supports an analytics application that processes the data and detects changes in real time. Thus, by detecting anomalies, the progression of the disease can be measured objectively without the need for scientists to focus on the underlying computing technologies. Physicians and researchers are intended to have access to the data as well as be able to submit their own anonymised patient data for analysis. According to [15] the correlation of data that quantifies symptoms such as slowness of movement, tremor, and sleep quality with molecular data could advance drug development and provide a deeper insight into the clinical course of Parkinson's disease.

MARG Sensors

MARG sensors is a collective term for magnetic, angular rate, and gravitational sensors that encompasses inertial sensors, as well as magnetic field sensors, also referred to as magnetometers. Inertial sensors generally fall into two categories: instruments sensing linear inertial displacement (accelerometers) and rotational inertial rate sensors (gyroscopes). They can be applied in various contexts to quantify vibration, motion, and shock [1]. Particularly, the development of microelectromechanical systems (MEMS) opened up many medical applications as mentioned in the previous Section 1.5.2. This chapter compiles the functional principles of MARG sensors and introduces inertial measurement units (IMUs) as a combination of those. At the end of the chapter the GaitWatch device is described in detail.

2.1 Accelerometers

Accelerometers measure the acceleration of an object relative to an inertial frame. Since acceleration cannot be measured directly, the force exerted to a reference mass is obtained and the resultant acceleration is computed according to Newton's second law $\mathbf{F} = m \cdot \mathbf{a}$, where \mathbf{F} denotes the three-dimensional force vector, m the mass, and \mathbf{a} the three-dimensional acceleration vector. Usually, an accelerometer consists of a small proof mass connected via a spring to the case of the instrument. The proof mass is displaced by Δx with respect to the case, when the instrument experiences a certain acceleration along its sensitive axis. Disregarding drag force, the displacement is directly proportional to the force exerted

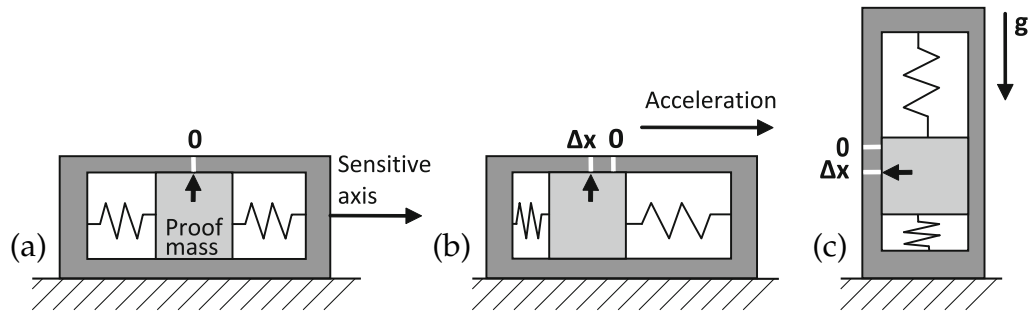


Figure 2.1: A mass-and-spring accelerometer under different conditions: (a) at rest or in uniform motion, (b) accelerating, and (c) at rest from [1].

by the mass and thus to the acceleration. Therefore, by measuring the displacement of the proof mass the acceleration can be obtained. Figure 2.1 shows the displacement of the mass in respect to the case of the instrument for three different conditions: (a) at rest or in uniform motion, (b) accelerating, and (c) at rest. In cases where the three-dimensional vector of the acceleration is required, three single-axis accelerometers are used. Although a mutually orthogonal mount is common practice, any non-coplanar arrangement is acceptable, as long as the angle between the sensitive axis are known [1].

2.2 Gyroscopes

Gyroscopes, also called angular rate sensors, measure angular velocity and are based on the Coriolis Effect. By integrating the angular velocity the rotation angle is obtained [16].

2.3 Magnetometers

Magnetometers measure the strength and the direction of the magnetic field in a point in space, using the relationship between magnetic fields, movement and induced currents [16].

2.4 Inertial Measurement Units

Devices using a combination of accelerometers and gyroscopes to measure the orientation of a solid body with up to six degrees of freedom are referred to as IMUs. If they include magnetic field sensors (magnetometers), they are termed magnetic inertial measurement units (MIMUs).

MIMUs are portable and relatively inexpensive. They can be easily attached to the body and thus allow non-clinical longterm application. Their drawbacks are complex calibration procedures and drift behaviour over time, depending on intensity and duration of the movement. Hence, in order to maintain a satisfactory degree of precision, periodical recomputation of the calibration parameters is required [16].

2.5 The GaitWatch

The above mentioned GaitWatch device we used to gather the movement data was designed to monitor the motion of patients while attached to the body. It was developed at the Department of Neurology of the Ludwig-Maximilians University in Munich, Germany, in association with the Department of Signal Theory, Telematics and Communications of the University of Granada, Spain. The system is composed of a set of embedded magnetic and inertial sensors wired to a box containing a microcontroller. This microcontroller is in charge of collecting data from the embedded box sensors, as well as from the external measurement units, and storing them on a memory card. The various units are placed at the patient's trunk, arms, thighs, and shanks as shown in Figure 2.2. The components of the three different kinds of subunits are described below:

- TYPE A – thighs and shanks:

IMU Analog Combo Board with 5 Degrees of Freedom [17], containing an IDG500 biaxial gyroscope, from which only y-axis is actually used, with a measurement range of $\pm 500^\circ/\text{s}$ [18] and a $\pm 3\text{ g}$ triaxial accelerometer, ADXL335 [19].

- TYPE B – arms:

IDG500 biaxial gyroscope with a measurement range of $\pm 500^\circ/\text{s}$ [18].

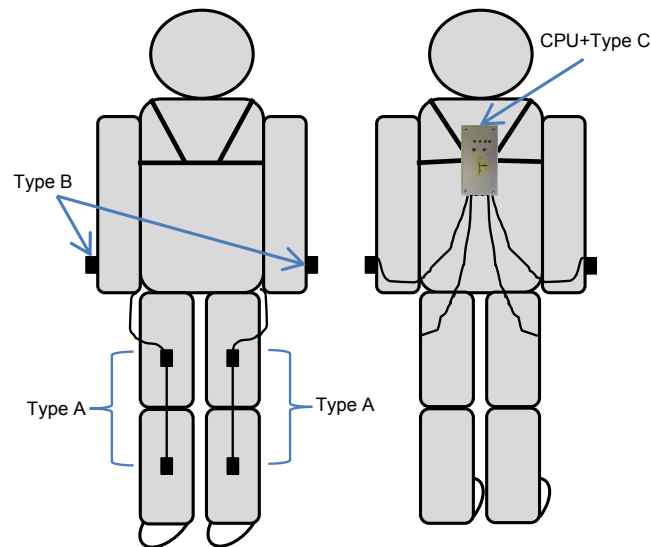


Figure 2.2: Placement of the GaitWatch components at the body from [2].

- TYPE C – trunk:

ADXL345 triaxial accelerometer with a programmable measurement range of $\pm 2/\pm 4/\pm 8/\pm 16$ g [20], IMU3000 triaxial gyroscope with a programmable measurement range of $\pm 250/\pm 500/\pm 1000/\pm 3000^\circ/\text{s}$ [21], Micromag3 triaxial magnetometer with a measurement range of ± 11 Gauss [22], AL-XAVRB board containing an AVR ATxmega processor [23].

Digital Filters

Conceived in general terms, a filter is a physical device for removing unwanted components of a mixture. In the technical field a filter is a system designed to extract information from noisy measurements of a process. That is, the filter delivers an estimate of the variables of principal interest, which is why it may also be called an estimator. Filter theory is applied in diverse fields of science and technology, such as communications, radar, sonar, navigation, and biomedical engineering [3].

In contrast to analogue filters that consist of electronic circuits to attenuate unwanted frequencies in continuous-time signals and thus extracted the useful signal, a digital filter is a set of mathematical operations applied to a discrete-time signal in order to extract information about the hidden quantity of interest. A discrete-time signal is a sequence of samples at equidistant time instants that represent the continuous-time signal with no loss, provided the sampling theorem is satisfied, according to which the sample frequency has to be greater than twice the highest frequency component of the continuous-time signal.

Digital filters can be classified as linear and nonlinear. If the quantity at the output of the filter is a linear function of its input, that is, the filter function satisfies the superposition principle, the filter is said to be linear. Otherwise, the filter is nonlinear.

3.1 The Filtering Problem

Consider, as an example involving filter theory, the continuous-time dynamical system depicted in Figure 3.1. The desired state vector of the

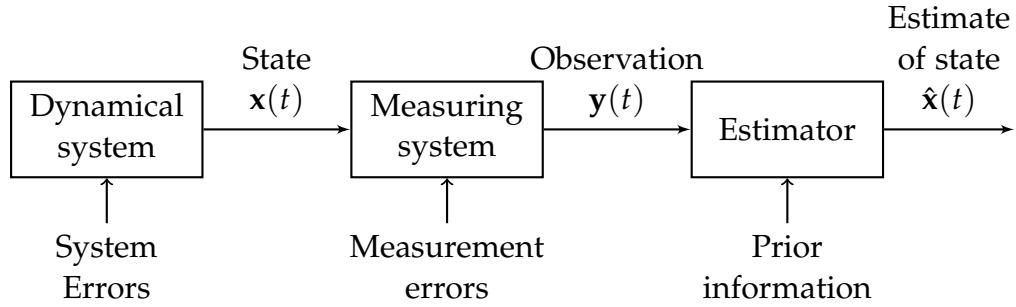


Figure 3.1: Block diagram depicting the components involved in state estimation from [3].

system, $\mathbf{x}(t)$, is usually hidden and can only be observed by indirect measurements $\mathbf{y}(t)$ that are a function of $\mathbf{x}(t)$ and subject to noise. Equally, the equation describing the evolution of the state $\mathbf{x}(t)$ is usually subject to system errors. These could be caused by, for instance, effects not accounted for in the model. The dynamical system may be an aircraft in flight, in which case the elements of the state vector are constituted by its position and velocity. The measuring system may be a tracking radar producing the observation vector $\mathbf{y}(t)$ over an interval $[0, T]$. The requirement of the filter is to deliver a reliable estimate $\hat{\mathbf{x}}(t)$ of the actual state $\mathbf{x}(t)$, by taking the measurement as well as prior information into account.

3.2 Wiener Filter

A statistical criterion, according to which the performance of a filter can be measured, is the mean-squared error. Consider the linear discrete-time filter with the impulse response w_0, w_1, w_2, \dots depicted in Figure 3.2. At some discrete time n it produces an output designated by $\hat{x}(n)$, which provides an estimate of a desired response denoted by $d(n)$. According to Haykin [3] the essence of the filtering problem and the resulting requirement is summarised with the following statement:

“Design a linear discrete-time filter whose output $\hat{x}(n)$ provides an estimate of the desired response $d(n)$, given a set of input samples $y(0), y(1), y(2), \dots$, such that the mean-square value of the estimation error $e(n)$, defined as the difference between the desired response $d(n)$ and the actual response $\hat{x}(n)$, is minimized.”

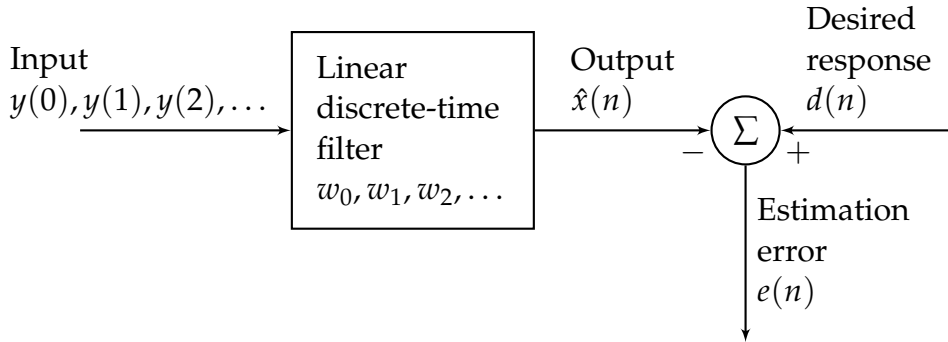


Figure 3.2: Block diagram representation of the statistical filtering problem from [3].

Assume a stationary stochastic process with known statistical parameters as the mean and correlation functions of the useful signal and the unwanted additive noise. Then, the solution to this statistical optimisation problem is commonly known as the Wiener filter. Yet, since the Wiener filter requires a priori information about the statistics of the data to be processed, it may not be optimum for non-stationary processes. For such an environment, in which the statistics are time-varying, it needs a filter that constantly adapts its parameters to optimise its output.

3.3 Adaptive Filters

A possible approach to mitigate the limitations of the Wiener filter for non-stationary processes is the ‘estimate and plug’ procedure. The filter ‘estimates’ the statistical parameters of the relevant signals and ‘plugs’ them into a non-recursive formula for computing the filter parameters. This procedure requires excessively elaborate and costly hardware for real-time operation [3]. To overcome this disadvantage one may use an adaptive filter, which is a self-designing system that relies, in contrast, on a recursive algorithm. It allows the filter to perform satisfactorily even if there is no complete knowledge of the relevant signal characteristics. Provided the variations in the statistics of the input data are sufficiently slow, the algorithm can track time variations and is thus suitable for non-stationary environments. The algorithm starts from some predetermined set of initial conditions respecting the knowledge about the system. In a stationary environment it converges to the optimum Wiener solution in

some statistical sense after successive iterations. The Kalman filter is such an adaptive filter.

Due to the fact that the parameters of an adaptive filter are updated each iteration, they become data dependent. The system does not obey the principles of superposition which therefore makes the adaptive filter in reality a nonlinear system. However, an adaptive filter is commonly said to be linear if its input-output map satisfies the superposition principle, as long as its parameters are held fixed. Otherwise it is said to be nonlinear.

3.4 Kalman Filter

The Kalman filter is a set of recursive mathematical equations that provides an efficient means to estimate the state of a linear dynamic system perturbed by additive white Gaussian noise, even when the precise nature of the modelled system is unknown. It incorporates knowledge of the system and measurement device dynamics, the statistical description of the system errors and measurement noise, uncertainty in the dynamics model, and available information about initial conditions of the variables of interest, to produce an estimate of these variables, in a way that the mean of the squared error is minimised [4].

The filter is named after Rudolf E. Kalman who 1960 published his famous paper describing a recursive solution to the discrete-data linear filtering problem [24]. Since that time, the Kalman filter has been the subject of extensive research, due, to a large extent, to the advances in digital computing [25]. It finds applications in autonomous and assisted navigation, more examples missing, among others.

The following introductory example from [4] is an illustrative description of the determination of a one-dimensional position to understand how the Kalman filter works.

3.4.1 An Introductory Example

Suppose you are lost at sea during the night and take a star sighting to determine your approximate position at time t_1 to be z_1 . Your location estimate is, due to inherent measurement device inaccuracies and human error, somewhat uncertain, and thus assumed to be associated with a standard deviation σ_{z_1} . The conditional probability of $x(t_1)$, your actual

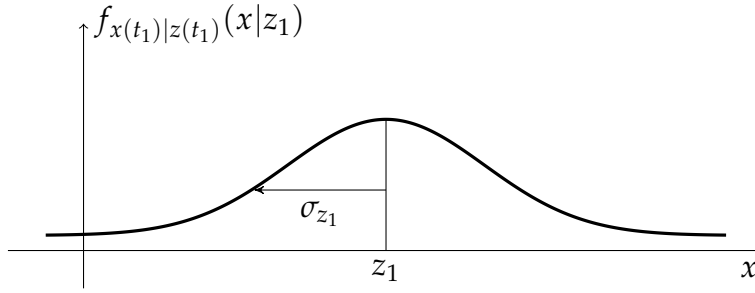


Figure 3.3: Conditional density of position based on measurement value z_1 from [4].

position at time t_1 , conditioned on the observed value z_1 , is depicted in Figure 3.3. The best estimate of your position, based on this conditional probability density, is

$$\hat{x}(t_1) = z_1 \quad (3.1)$$

and the variance of the error in the estimate is

$$\sigma_x^2(t_1) = \sigma_{z_1}^2. \quad (3.2)$$

Right after you, say a trained navigator friend takes an independent fix at time $t_2 \cong t_1$, so that the true position has not changes at all. He obtains a measurement z_2 with a variance σ_{z_2} , which is somewhat smaller than yours, since he has a higher skill. Figure 3.4 depicts the conditional density of your position at time t_2 , based only on the measurement value z_2 . Combining these data, your position at time $t_2 \cong t_1$, $x(t_2)$, given both z_1 and z_2 , is then a Gaussian density with mean μ and variance σ^2 , as indicated in Figure 3.5, with

$$\mu = z_1 \frac{\sigma_{z_2}^2}{\sigma_{z_1}^2 + \sigma_{z_2}^2} + z_2 \frac{\sigma_{z_1}^2}{\sigma_{z_1}^2 + \sigma_{z_2}^2} \quad (3.3)$$

and

$$\frac{1}{\sigma^2} = \frac{1}{\sigma_{z_1}^2} + \frac{1}{\sigma_{z_2}^2}. \quad (3.4)$$

The uncertainty in your estimate of position has been decreased because σ is less than either $\sigma_{z_1}^2$ or $\sigma_{z_2}^2$. Even if σ_{z_1} was very large, the variance of the estimate is less than σ_{z_2} , which means that even poor quality data

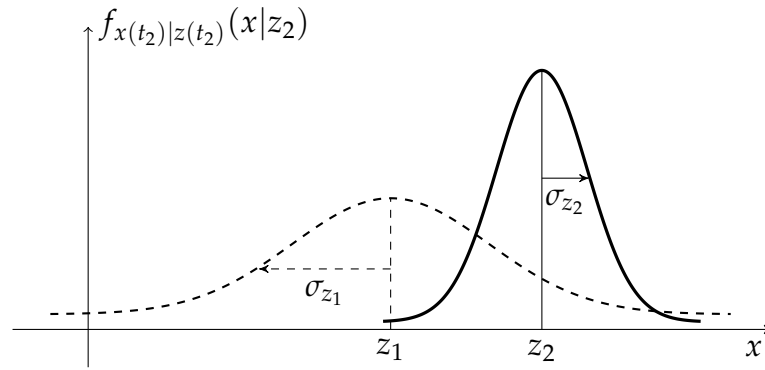


Figure 3.4: Conditional density of position based on measurement value z_2 alone from [4].

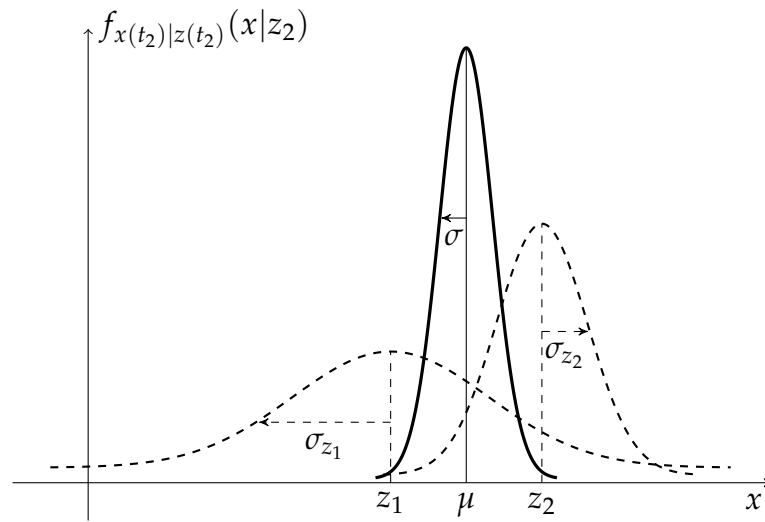


Figure 3.5: Conditional density of position based on data z_1 and z_2 from [4].

increases the precision of the filter output. The best estimate, given this density, is

$$\hat{x}(t_2) = \mu, \quad (3.5)$$

with an associated error variance σ^2 .

Having a closer look at the form of μ in Equation 3.3, one notices that it makes good sense. If the measurements were of equal precision, meaning $\sigma_{z_1} = \sigma_{z_2}$, the optimal estate is simply the average of both measurements, as would be expected. If σ_{z_1} is larger than σ_{z_2} , the equation weights z_2 more heavily than z_1 .

Equation 3.5 for the filter output can be written as

$$\begin{aligned} \hat{x}(t_2) &= z_1 \frac{\sigma_{z_2}^2}{\sigma_{z_1}^2 + \sigma_{z_2}^2} + z_2 \frac{\sigma_{z_1}^2}{\sigma_{z_1}^2 + \sigma_{z_2}^2} \\ &= z_1 + \frac{\sigma_{z_1}^2}{\sigma_{z_1}^2 + \sigma_{z_2}^2} [z_2 - z_1] \end{aligned} \quad (3.6)$$

or in a form that is used in Kalman filter implementations, with $\hat{x}(t_1) = z_1$, as

$$\hat{x}(t_2) = \hat{x}(t_1) + K(t_2)[z_2 - \hat{x}(t_1)], \quad (3.7)$$

where

$$K(t_2) = \frac{\sigma_{z_1}^2}{\sigma_{z_1}^2 + \sigma_{z_2}^2}. \quad (3.8)$$

These equation represent the ‘predictor-corrector’ structure of the Kalman filter. A prediction of the value that the desired variables and the measurements will have at the next measurement time is made, based on all previous information. Then the difference between the measurement and its predicted value is used to correct the prediction of the desired variables. According to Equation 3.7 the optimal estimate at time t_2 , $\hat{x}(t_2)$, is equal to $\hat{x}(t_1)$, the best prediction of its value before z_2 is taken, plus a correction term of an optimal weighting value times the difference between z_2 and the best prediction of it before the measurement is actually taken.

To incorporate dynamics into the model, suppose you travel for some time before taking another measurement. The best model you have for your motion may be of the form

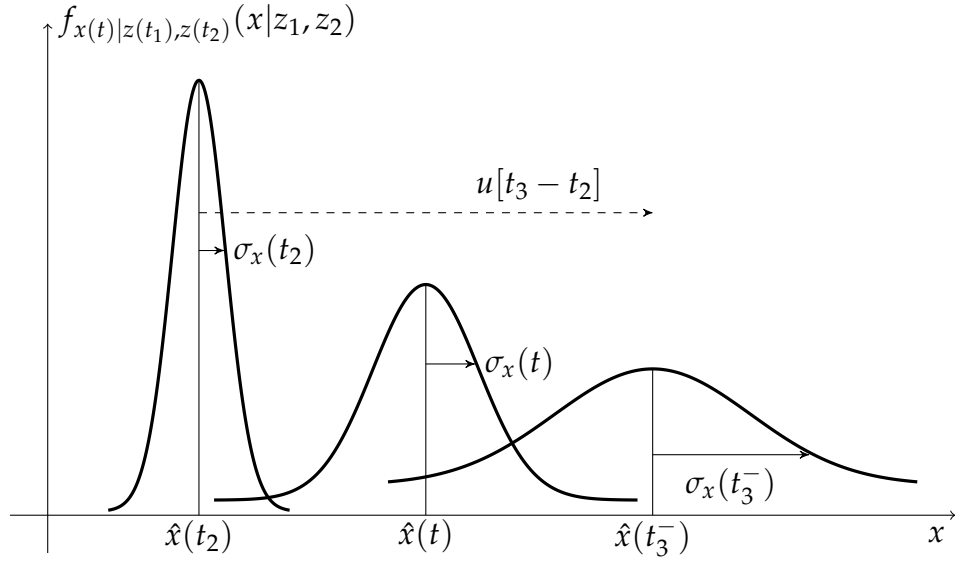


Figure 3.6: Propagation of conditional probability density from [4].

$$\frac{dx}{dt} = u + w, \quad (3.9)$$

where u is a nominal velocity and w is a noise term, representing the uncertainty in your knowledge of the actual velocity due to disturbances and effects not accounted for in the simple first order equation. It will be modeled as white Gaussian noise with a mean of zero and variance of σ_w^2 .

The conditional density of the position at time t_2 , given z_1 and z_2 , was previously derived. Figure 3.6 shows graphically how the density travels along the x -axis as time progresses. It start at the best estimate and moves according to the above mentioned model of dynamics. Due to the constant addition of uncertainty over time it spreads out. As the variance becomes greater you become less sure of your position. The Gaussian density $f_{x(t_3)|z(t_1),z(t_2)}(x|z_1,z_2)$ can be expressed mathematically by its mean and variance given by

$$\hat{x}(t_3^-) = \hat{x}(t_2) + u[t_3 - t_2] \quad (3.10)$$

$$\sigma_x^2(t_3^-) = \sigma_x^2(t_2) + \sigma_w^2[t_3 - t_2] \quad (3.11)$$

$\hat{x}(t_3^-)$ is the optimal prediction of the location at t_3^- before the measurement is taken at t_3 , associated with the variance in this prediction, $\sigma_x^2(t_3^-)$.

Now a measurement z_3 with an assumed variance $\sigma_{z_3}^2$ is taken. As before, its conditional probability density is combined with the density with mean $\hat{x}(t_3^-)$ and variance $\sigma_x^2(t_3^-)$, to yield a Gaussian density with mean

$$\hat{x}(t_3) = \hat{x}(t_3^-) + K(t_3)[z_3 - \hat{x}(t_3^-)] \quad (3.12)$$

and variance

$$\sigma_x^2(t_3) = \sigma_x^2(t_3^-) - K(t_3)\sigma_x^2(t_3^-), \quad (3.13)$$

where the gain $K(t_3)$ is given by

$$K(t_3) = \frac{\sigma_x^2(t_3^-)}{\sigma_x^2(t_3^-) + \sigma_{z_3}^2}. \quad (3.14)$$

Observing the form of Equation 3.14 the reasonableness of the filter structure becomes obvious. If the variance of the measurement noise $\sigma_{z_3}^2$ is large, then $K(t_3)$ is small, meaning that little confidence is put in a very noisy measurement and that it is weighted lightly. For $\sigma_{z_3}^2 \rightarrow \infty$, $K(t_3)$ becomes zero, and $\hat{x}(t_3)$ equals $\hat{x}(t_3^-)$. Thus, an infinitely noisy measurement is totally ignored. Likewise, if the dynamical system noise variance σ_w^2 is large, then according to Equation 3.11, $\sigma_x^2(t_3^-)$ will be large, and so will be $K(t_3)$. Therefore, the measurement is weighted heavily, in case you are not very certain about the output of the system model within the filter structure. In the limit as $\sigma_w^2 \rightarrow \infty$, $\sigma_x^2(t_3^-) \rightarrow \infty$, and $K(t_3) \rightarrow 1$, so Equation 3.5 yields

$$\hat{x}(t_3) = \hat{x}(t_3^-) + 1 \cdot [z_3 - \hat{x}(t_3^-)] = z_3. \quad (3.15)$$

That means that in the limit of absolutely no confidence in the system model output, solely the new measurement is taken as the optimal estimate. Finally, if you are absolutely sure of your estimate before z_3 comes available, $\sigma_x^2(t_3^-)$ would become zero, and so would $K(t_3)$, which means that the measurements would be left disregarded.

Extending Equations 3.10, 3.11, 3.12 and 3.14 to the vector case and allowing time varying parameters in the system and noise description leads to the general Kalman filter equations.

3.4.2 Formulation of the Kalman Filter Equations

Let $\mathbf{x} \in \mathbb{R}^n$ be the state vector of a discrete-time controlled process governed by the linear stochastic difference equation

$$\mathbf{x}_k = \Phi_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_{k-1}\mathbf{u}_{k-1} + \mathbf{w}_{k-1} \quad (3.16)$$

and $\mathbf{z}_k \in \mathbb{R}^m$ the observation or measurement vector of this process, given by

$$\mathbf{z}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{v}_k, \quad (3.17)$$

where the index $k \in \mathbb{N}^0$ denotes discrete time normalised to the sampling interval. The $n \times 1$ vector w_k and the $m \times 1$ vector v_k represent the process noise and the measurement noise, respectively, modelled as zero-mean, Gaussian white noise

$$\mathbf{w}_k \sim N(0, \mathbf{Q}_k), \quad (3.18)$$

$$\mathbf{v}_k \sim N(0, \mathbf{R}_k), \quad (3.19)$$

with the process noise covariance matrix \mathbf{Q}_k and the measurement noise covariance matrix \mathbf{R}_k . They are assumed to be uncorrelated. The $n \times n$ transition matrix Φ_k in 3.16 relates the state at the previous time step $k-1$ to the state at the current step k . The $n \times l$ matrix \mathbf{B}_k relates the optional control input $\mathbf{u}_k \in \mathbb{R}^l$ to the state \mathbf{x}_k . Finally, the $m \times n$ measurement matrix \mathbf{H}_k in 3.17 relates the state \mathbf{x}_k to the measurement \mathbf{z}_k .

The Kalman filter solves the problem of estimating the state \mathbf{x}_k of the given linear stochastic system, represented by $\hat{\mathbf{x}}_k$, which is also a linear function of the measurement \mathbf{z}_k , minimising the weighted mean-squared error. This problem is called the *linear quadratic Gaussian* estimation problem; the dynamic system is linear, the performance cost function is quadratic, and the random process is Gaussian.

We define the vector $\hat{\mathbf{x}}_k^- \in \mathbb{R}^n$ as the *a priori* state estimate representing knowledge of the process prior to step k and $\hat{\mathbf{x}}_k \in \mathbb{R}^n$ as the *a posteriori* state estimate at step k given the measurement \mathbf{z}_k :

$$\hat{\mathbf{x}}_k^- = \Phi_{k-1}\hat{\mathbf{x}}_{k-1} + \mathbf{B}_{k-1}\mathbf{u}_{k-1}, \quad (3.20)$$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \mathbf{K}_k[\mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_k^-]. \quad (3.21)$$

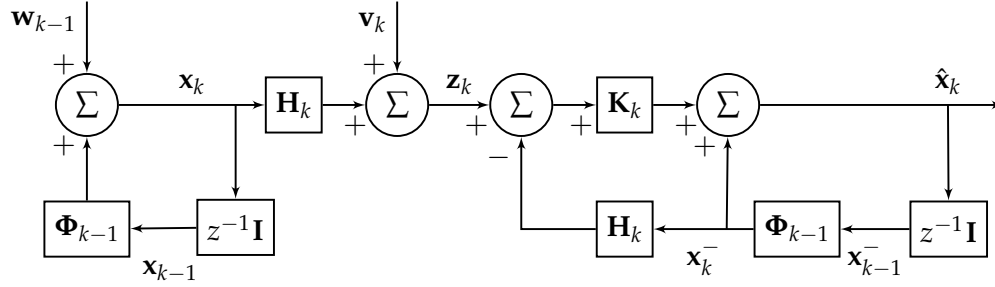


Figure 3.7: Block diagram depicting the relation between a discrete-time dynamical system, its observation, and the Kalman filter.

The term $[\mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_k^-]$ is called the measurement innovation or residual. It reflects the discordance between the predicted measurement $\mathbf{H}_k \hat{\mathbf{x}}_k^-$ and the actual measurement \mathbf{z}_k . The $n \times m$ matrix \mathbf{K}_k is termed the Kalman gain and is given by

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T [\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k]^{-1}, \quad (3.22)$$

with

$$\mathbf{P}_k^- = \Phi_{k-1} \mathbf{P}_{k-1} \Phi_{k-1}^T + \mathbf{Q}_{k-1} \quad (3.23)$$

and

$$\mathbf{P}_k = [\mathbf{I} - \mathbf{K}_k \mathbf{H}_k] \mathbf{P}_k^-. \quad (3.24)$$

Figure 3.7 illustrates the relation of the Kalman filter to the discrete-time dynamical system, where z^{-1} denotes the unit-delay and \mathbf{I} the $n \times n$ identity matrix.

The Kalman filter equations can be divided into two groups: *time update* Equations 3.20, 3.23 and *measurement update* Equations 3.21, 3.22, and 3.24, as seen in Figure 3.8, which shows the predict and update behaviour of the filter algorithm.

3.5 Extended Kalman Filter

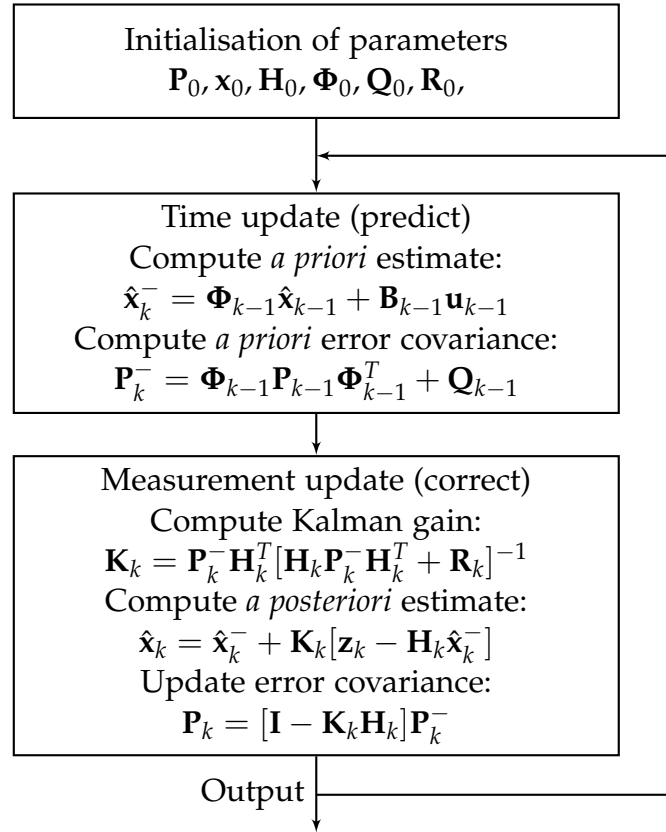


Figure 3.8: Operation cycle of Kalman filter algorithm depicting predict and correct behaviour.

Chapter 4

Implementation

4.1 Realisation in Matlab

4.2 Experiments

4.3 Results

4.4 Discussion

Conclusion and Future Work

5.1 Conclusions

Summarising the above, I can say that I have learned a lot in the four month that I spent in Granada. Amongst others I have come to know many new work methods, not only due to being exposed to people from a different culture, but also due to the fact that scientific research differs strongly from the work as a student at university. I gained a deeper understanding of orientation estimation and how Kalman filtering improves those. Therefore I had to study the principles of Kalman filters as well as the basics of MARG sensors. I was able to improve my MATLAB® skills and have realised how important it is to write understandable and well commented code, if it is for a larger project and not only for a course-work. I am now familiar with tools such as GitHub and Pivotal Tracker which make working in a team much easier and significantly more efficient. Beside my work at the research centre, where I obtained a valuable insight into scientific research, I read a book about scientific writing that helped me to improve my oral and written English skills during my stay. Furthermore I now know the fundamentals of L^AT_EX.

All in all it was a great experience, professionally as well as personally. I truly and unreservedly recommend such a stay to every university student.

5.2 Future Work

Biomedical research is a very interesting blend of both my major interests, that is, working in the medical field as a paramedic and in the technical field as an electrical engineer. There is a variety of possible future work. One related topic would be the validation of the pitch angles measured with the gyroscopes of the GaitWatch by means of cameras that record the trace of visual markers. From these markers one could compute the pitch angels and compare them to the those of the GaitWatch.

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