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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

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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, 20th 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.

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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
MIMU	Magnetic inertial measurement unit

Notation

MSE	Mean squared error
$\mathbf{x}(t)$	Actual state vector of a continuous-time dynamical system at time t.
$\hat{\mathbf{x}}(t)$	Estimated state vector of a continuous-time dynamical system at time t.
$\hat{\mathbf{x}}_i$	
$\mathbf{y}(t)$	Observation vector of a continuous-time dynamical system at time t.

Chapter 1

Introduction

1.1 General

Human body motion analysis has become an integral part of medical diagnostic techniques.

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 [3] to improve the estimation of orientation angles by means of inertial sensors.

1.4 Methodology

Our Team was composed of three members and worked using the agile software development methodology. Working software was delivered frequently and was the principal measure of progression. To follow the progress of other team members 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. I used the document markup language LaTeX to write this thesis.

1.5 Document Structure

This thesis begins with an introductory chapter where the scope of the concrete task is discussed as well as its goals and ends with the hardware we used. Chapter 2 describes the state of the art. In Chapter 3, we will elaborate on the Fundamentals necessary for the implementation. Chapter 4 presents and discusses the results. Finally, Chapter 5 concludes and proposes possible future work.

Chapter 2

State of the Art

The state of the art at the commencement of the project is described below.

Chapter 3

MARG Sensors

MARG sensors is a collective term for magnetic, angular rate, and gravitational sensors. It encompasses inertial sensors, such as accelerometers and gyroscopes, as well as magnetic field sensors, also referred to as magnetometers. 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.

MARG sensors have numerous applications in navigation. They are used in

3.1 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 $\mathbf{F} = m \cdot \mathbf{a}$ [**?**]. Microelectromechanical systems (MEMS) accelerometer

3.2 Gyroscopes

Gyroscopes measure angular velocity and are based on the Coriolis Effect. By integrating the angular velocity the rotation angle is obtained [4].

3.3 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 [4].

3.4 Inertial Measurement Units

Inertial sensors are sensors based on inertia.

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 [4].

3.5 GaitWatch

The MIMU we used to gather the movement data is called GaitWatch, a device 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 3.1. 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 [5], containing an IDG500 biaxial gyroscope, from which only y-axis is actually

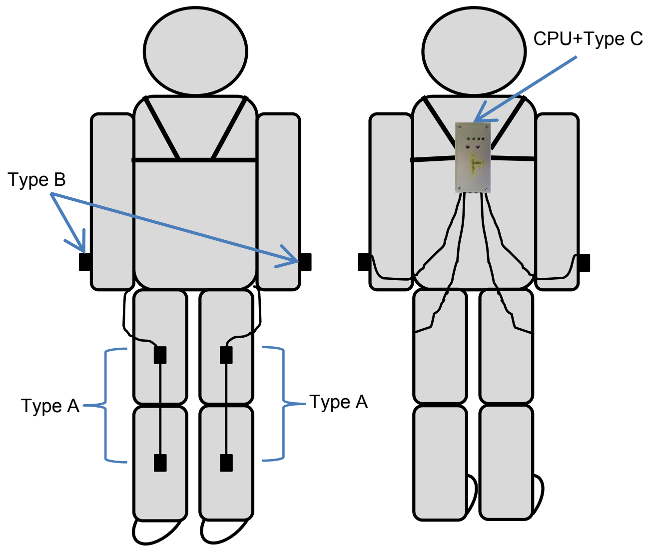


Figure 3.1: Placement of GaitWatch components at the body [1].

used, with a measurement range of ±500 °/s [6] and a ±3 g triaxial accelerometer, ADXL335 [7].

- Type B – arms:

  IDG500 biaxial gyroscope with a measurement range of ±500 °/s [6].

- Type C – trunk:

  ADXL345 triaxial accelerometer with a programmable measurement range of ±2/±4/±8/±16 g [8], IMU3000 triaxial gyroscope with a programmable measurement range of ±250/±500/±1000/±3000°/s [9], Micromag3 triaxial magnetometer with a measurement range of ±11 Gauss [10], AL-XAVRB board containing an AVR ATxmega processor [11].

Chapter 4

The Kalman Filter

4.1 The Filtering Problem

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, distorted data. 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 [2].

Consider, as an example involving filter theory, the continuous-time dynamical system depicted in Figure 4.1. The desired state vector of the 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. 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 is to deliver a reliable estimate $\hat{\mathbf{x}}(t)$ of the state $\mathbf{x}(t)$, taking prior information into account.

4.2 Digital Filters

In contrast to analogue filters that consist of electronic circuits to attenuate unwanted frequencies in continuous-time signals and thus extracted the

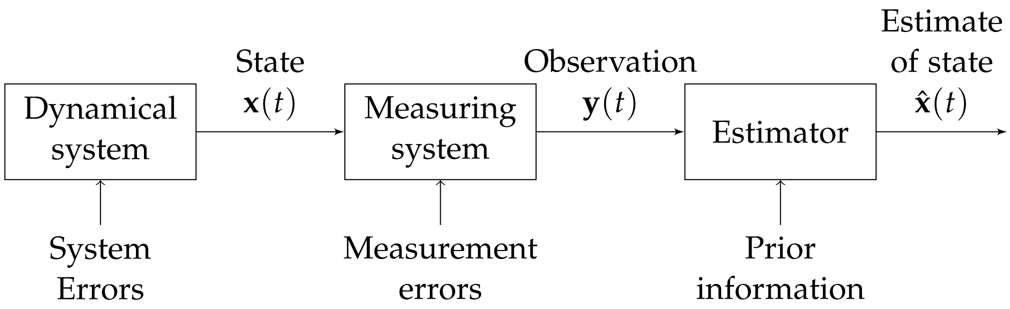


Figure 4.1: Block diagram depicting the components involved in state estimation adopted from [2].

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 sequence of samples at equidistant time instants 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.

4.2.1 Wiener Filter

A statistical criterion according to which the performance of a filter can be measured is the mean-squared error, defined as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{x}_i - x_i)^2$$

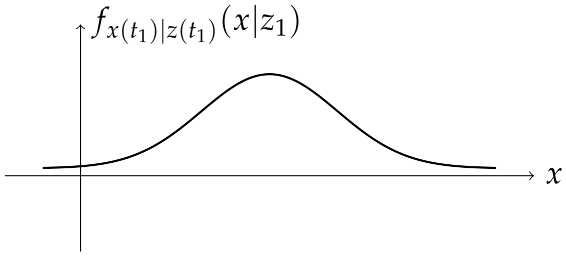
where i denotes the element of the vector $\hat{\mathbf{x}}$ and the actual state vector $\mathbf{x}$ with a length of n, respectively. Assuming a stationary stochastic process with known statistical parameters as the mean and correlation functions of the useful signal and the unwanted additive noise, the so-called Wiener filter is said to be optimum as it minimises the mean-square value of the error signal. Since the Wiener filter requires apriori information about the statistics of the data to be processed, it may not be optimum for non-stationary processes.

4.2.2 Adaptive Filters

4.2.3 Kalman Filters

The following simple example from [12] is no complete mathematical derivation but an illustrative description of the determination of a one-dimensional position to understand how the Kalman filter works.

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 is σ_{z_1}. The conditional probability of $x(t_1)$, your actual position at time t_1, conditioned on the observed value z_1, is depicted in Figure



4.3 Orientation Estimation

Chapter 5

Implementation

5.1 Realisation in Matlab

5.2 Experiments

5.3 Results

5.4 Discussion

Chapter 6

Results and Discussion

Chapter 7

Conclusion and Future Work

7.1 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 Parkinson's disease and how various gait analysis techniques are used to quantify its effects. Therefore I had to study the principles of force plates and inertial measurement units as well as the basics of classification. 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 coursework. 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 LaTeX.

The above will hopefully serve as a good foundation for my subsequent bachelor's thesis. All in all it was a great experience, professionally as well as personally. I truly recommend such a stay to every university student.

7.2 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. I would like to keep working in this field and write my aforementioned bachelor's thesis here in Granada. 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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