Dedicated to my parents, wife and family

ABSTRACT

The Kalman filter is a mathematical powerful tool that is playing an increasingly important role in a number of applications e.g.: missile tracking, parametric estimation etc. While the Kalman filter has been around for about 30 years, it proved to be the best possible estimator for a large class of problems. Kalman filtering addresses an age-old question: How do you get accurate information out of incomplete data? More pressingly, how do you update a "best" estimate for the state of a system as new, but still incomplete, data pour in?, the Kalman filter is designed to strip unwanted noise (errors) from data which is time dependant. The applications of Kalman Filter are endless. Kalman filtering has proved useful in navigational and guidance systems, radar tracking, sonar ranging, and satellite orbit determination. Kalman original paper (1960) has generated thousands of other papers on aspects and applications of filtering. This work has also stimulated mathematical research in such areas as numerical methods of linear algebra.

The Extended Kalman Filter (EKF) has become a standard technique used in a number of nonlinear estimation and machine learning applications. These include estimating the state of a nonlinear dynamic system.

In this thesis the Kalman filter equations have been proved based on the traditional sequential least squares method of least squares. A program is written to solve a simple inertial survey problem. The technique proved to be most suitable. However, in more complicated problems the formation of the transition matrix might prove to be difficult. For better

understanding of the filter techniques, examples of applications of the Kalman filter in navigation and traffic tracking are discussed.

ACKNOWLEDGEMENTS

I would like to express my deep gratitude and thanks to my Supervisor Dr. Ali Hassan Fagir for his kind help, close supervision, valuable suggestions, and discussions. Special thanks to Surveying Engineering Department staff, College of Engineering, Sudan University of Science and Technology.
Further more I would like to thank Engineer Hamid Mahmoud Wakeel, National Highway Authority General manager for his considerable help during all stags of my study. Also I like to thank every one in the National Highway Authority who helps me during my study, Special thanks to training department.

CONTENTS

DEDICATION……..…….i

ABESTRACT…….. ii

ACKNOWLEDGEMENT……..……iii

CONTENTS…….……iv

LIST OF FIGURES…….……vi

CHAPTER ONE: INTRODUCTION…….1

CHAPYER TWO: LEAST SQUARES ESTIMATION THEORY

2-1 The general concept of least squares estimation …….……..…..3

2-2 Mathematical models for least square estimation……..…3

2-2-1 Derivation of the method……...…8

2-2-2 Summary of least squares formulae……..… 9

2-3 sequential and step by step least squares methods……..…...10

2-3-1 Sequential least squares…….10

2-3-1-1 Sequential least squares procedure…… 10

2-3-1-2 Examples of sequential least squares applications ……11

2-3-2 Step by step (Helmert-Wolf) method ……...…11

2-3-2-1 Step by step (Helmert-Wolf) procedure…….11

2-3-2-2 Examples of step by step (Helmert-Wolf) applications…….13

CHAPTER THREE: THE KALMAN FILTER

3-1The concept of filtering, smoothing and prediction……14

3-2 The filter process ……..15

3-3 The Kalman filter……...17

3-3-1 Derivation of the linear Kalman filter based on least squares……19
3-3-2 Summary of the linear Kalman Filter algorithm……24
3-3-3 Some numerical aspects…….27
3-4 The nonlinear Kalman filter……..27
CHAPTER FOUR: APPLICATIONS OF THE KALMAN FILTER
4-1 Navigation……..30
4-2 Traffic Tracking…….34
4-3 Inertial Surveying……...35
4-4 GPS Navigation…….36
4-4-1 General…….36
4-4-2 Application of the Kalman filter in GPS……37
4-5 Other Kalman filter applications……...44
CHAPTER FIVE: TESTS AND RESULTS
5-1 The filter simulation……45
5-2 The filter tests…..……..45
5-3 Results……..……..50
CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS
6-1 Conclusion……..52
6-2 Recommendations……..……53
APPENDICES
Appendix A the computer program…….……55
A-1 Source Code…….……55
A-2 The Interactive desktop of the program……..…….61
A-3 The initial data used ……...…… 62
A-4 The coordinates data used……..……...…..…… 63
A-5 The Kalman filter estimation for the input data……..……64
A-6 Sample of statistical output of the program…….……65
Appendix B Numerical Examples…….…..…….66
B-1 off shore navigation example……...…...66
B-2 Traffic tracking example……...…….…….68
REFRENCES AND BIBLIOGRAPHY…….……71

LIST OF FIGURES

Figure No		Page No
Figure (2-1)	least square estimation for a linear model	**5**
Figure (2-2)	least square estimation for anon-linear model	**5**
Figure (2-3)	the two groups of measurements with the common area	**11**
Figure (3-1)	The general concept of filtering, smoothing and prediction	**15**
Figure (3-2)	The basic operation of the Kalman filter	**18**
Figure (3-3)	The ongoing discrete Kalman filter cycle. The time update projects The current state estimate ahead in time. The measurement update adjusts the projected estimate by an actual measurement at that time	**25**
Figure (3-4)	A complete picture of the operation of the Kalman filter, combining the high-level diagram of Figure 4.3 with the equations from (4-55) to (4-62).	**26**

Figure (4-1)	off shore positioning	**31**
Figure (4-2)	vehicle tracking using photos	**34**
Figure (5-1)	First simulation for the measurement weight matrix: The filter responds to measurements quickly, increasing the estimate variance	**46**
Figure (5-2)	Second simulation for the measurement weight matrix: The filter result is smooth path than the first simulation	**47**
Figure (5-3)	Third simulation for the measurement weight matrix: The filter is slower to respond to the measurements, resulting in reduced estimate variance.	**47**
Figure (5-4)	First simulation for the model weight matrix: The filter is slow to respond to the measurements, resulting in reduced estimate variance.	**48**
Figure (5-5)	Second simulation for the model weight matrix: The filter is slower to respond to the measurements, resulting in reduced estimate variance	**49**
Figure (5-6)	Third simulation for the model weight matrix: The filter responds to measurements quickly,	**49**
Figure (5-7)	After 12 iterations, our initial (rough) error Choice of the initial variance has settled to about 0.792579	**50**