The Pennsylvania State University

The Graduate School

STEREO VISION FOR AUTONOMOUS GROUND-BASED

TRACKING OF MIGRATING RAPTORS

A Thesis in

Aerospace Engineering

by

Sana Sarfraz

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science

August 2008

I grant The Pennsylvania State University the non-exclusive right to use this work for the University's own purposes and to make single copies of the work available to the public on a not-for-profit basis if copies are not otherwise available.

_____
Sana Sarfraz

The thesis of Sana Sarfraz was reviewed and approved[*] by the following:

Jacob W. Langelaan
Assistant Professor of Aerospace Engineering
Thesis Advisor

Joseph F. Horn
Associate Professor of Aerospace Engineering

George A. Lesieutre
Professor and Head of Aerospace Engineering

Abstract

MIGRATION PLACES extreme demands on birds as they travel long distances. Factors influencing when and where migrating birds stop to feed are not well understood, and may include internal conditions such as amount of body fat and external conditions such as local weather. By collecting data on individual behavior in response to internal and external conditions researchers will be able to build models of bird behavior and identify critical habitats along migration routes. The following thesis presents the design and simulation of a system of stereo cameras and processors, to enable the distributed, autonomous tracking of migratory raptors in order to facilitate the study of their flight patterns. The motivation behind this study is to map the migratory routes of raptors and other endangered species of birds. The knowledge of migratory routes will aid biological research, conservation efforts and shed light on whether man-made structures like windmills along these routes pose a threat to migrating birds or if raptors are able to alter their flight patterns to avoid collision. A cost effective method that can continuously monitor the flight path of birds around the observation site with minimal or no human input, can provide valuable information about the migratory patterns of the birds without incurring the cost of employing more people or buying specialized equipment. The proposed system, consisting of a set of off-the-shelf cameras and processors, would not require a great deal of fiscal or labor input while providing an accurate estimate of bird migration patterns.

Observation points may be set up along the ridge to obtain bearings to birds that come into view in order to compute their position and velocity at every time interval, using Kalman Filter based tracking algorithms. The accuracy of the estimates is lowered due to the Dilution of Precision, DOP introduced into the measurements because of the large distances between the birds and the camera systems. The tracking system proposed in this thesis consists of a number of stations each

composed of a camera pair and a processor, set up in a user specified geometry, along the ridge under observation. The estimation process is further complicated by the fact that the relations between the bird position and the bearings to it, utilize trigonometric properties, making the measurement model non-linear. A non-linear estimation method is therefore required.

Each station computes an initial estimate of the position and velocity of the birds viewed by its cameras using a Particle Filter and further tracking is carried out by the Unscented Kalman Filter. Data association between measurements is performed from camera to camera in each stereo set and from frame to frame between one time step and the next. The estimates from each station are transmitted to a master computer that computes the association of local estimates to each other before fusing all the independent estimates to any particular bird and transmitting the resulting final estimate back to all the stations. Results of Monte Carlo simulations show the convergence of the estimated error to the true error for estimates from one or more stations. The tracking system provides fairly accurate estimates under realistic constraints and may be implemented with readily available hardware.

Table of Contents

List of Figures

List of Tables

Acknowledgments

While all that is found on the pages that follow can be traced directly back to myself, the intellectual content of this thesis is the result of a non-Markovian process, and it owes its evolution to the inputs of my teachers, friends and family. I would like to take the opportunity to express my gratitude to some of the individuals who have led me to the completion of my thesis.

In particular, I would like to thank Dr. Jack Langelaan for giving me the opportunity to work on this project and guiding me through it. I have benefited greatly from his ability to simplify difficult concepts, which has helped me reach goals that seemed abstract at first glance by taking one tangible step at a time. I am grateful not only for the intellectual freedom I have enjoyed through the course of this research but also for the door always open to a puzzled graduate student.

I would like to thank Dr. Horn, for reviewing my thesis and offering his insightful and valued suggestions.

I would like to thank Sean Quinn Marlow for exchanging ideas with me and offering his perspective whenever sought, and Sade Sparbanie for conversation and camaraderie.

My friends, Greeshma, Sandhya and Shafique, have pampered me, pushed me, picked me up and supported me since I have known them and all the more over the course of my graduate studies. I cannot thank them enough and therefore will not attempt to.

My family has encouraged me to make the best of these years at school. I would like to acknowledge my sister, Farah and my uncle Gagmama, for their backing and sound advice. Lastly, I would like to express how fortunate I am to have parents like my own. The high expectations that they have from me are bolstered by their constant belief in me and their undiminished support of any choice I make in my professional and personal life. This thesis is dedicated to my Mom and Dad and I hope that it finds a place on our refrigerator.

Dedication

To my parents.

Chapter 1

Introduction

THE FOLLOWING THESIS presents the design and simulation of a system of stereo cameras and processors, to enable the distributed, autonomous tracking of migratory raptors in order to facilitate the study of their flight patterns. The motivation behind this study is to map the migratory routes of raptors and other endangered species of birds. The knowledge of migratory routes will aid biological research, conservation efforts and shed light on whether man-made structures like wind turbines along these routes pose a threat to migrating birds or if raptors are able to alter their flight patterns to avoid collision.

Observation points may be set up along the ridge to obtain bearings to birds that come into view in order to compute their position and velocity at every time interval, using Kalman Filter based tracking algorithms. The accuracy of the estimates is lowered due to the Dilution of Precision, DOP introduced into the measurements because of the large distances between the birds and the camera systems. Having a well distributed set of sensors can lower the DOP but installing sensors far away from the central processor can prove to be difficult, having multiple processors in a Distributed Estimation setup will solve this problem. The estimation process is further complicated by the fact that the relations between the bird position and the bearings to it, utilize trigonometric properties, making the measurement model non-linear. A non-linear estimation method is therefore required. The Kalman Filter is the optimal linear filter but variations of the Kalman Filter, that have previously been used successfully in non-linear estimation problems, are described and implemented.

The tracking system proposed in this thesis consists of a number of stations each composed of a camera pair and a processor, set up in a user specified geometry, along the ridge under observation. Each station computes an initial estimate of the position and velocity of the birds viewed by its cameras using an Particle Filter and further tracking is carried out by the Unscented Kalman Filter. The estimates from each station are transmitted to a master computer that fuses all the independent estimates and transmits the resulting estimate back to all the stations. Results of Monte Carlo simulations show the convergence of the estimated error to the true error for estimates from one or more stations. This thesis aims to accomplish the following tasks:

- Prepare a mathematical framework that describes the environment and facilitates the study of flight patterns. This involves selecting the states to be estimated, modeling bird dynamics and creating a model for obtaining bearing measurements from a set of cameras.

- Discuss methods that can be used to carry out the tracking, given the nonlinear and distributed nature of the system.

- Describe the implementation of the proposed tracking system and providing justification for the methods selected.

- Present the results depicting the performance of the system under a Monte-Carlo test consisting of simulations of several varying flight paths. The tested aspects are the track initiation, accuracy of estimates, correlation between true and predicted error and the data association

Figure 1.1. A satellite image of the Appalachian Mountains in Pennsylvania.

1.1 Motivation

Migration places extreme demands on birds as they travel long distances [1]. The ability to conserve energy through the use of atmospheric lift is crucial for successful migration. The long ridges of the Appalachian Mountains in Pennsylvania are a critical migration corridor for North American raptors and songbirds. Over 150 species use this migration corridor [2], and some ridges are renowned for local concentrations of hawks and eagles. An estimated 800 Golden Eagles migrate through Pennsylvania each year, with many of them passing by Tussey Mountain (approximately 10km east of Penn State's University Park campus). Factors influencing when and where they stop to feed are not well understood, and may include internal conditions such as amount of body fat and external conditions such as local weather. By collecting data on individual behavior in response to internal and external conditions researchers will be able to build models of bird behavior and identify critical habitats along migration routes.

Wind power development and associated wind turbines are increasing throughout the U.S., and there is great interest in establishing the infrastructure to use wind as a renewable energy source in Pennsylvania. Wind turbines are often established along mountain ridges: in Pennsylvania these ridges are also prime migration routes. Biologists have expressed concerns that wind turbines can result in direct mortality and avoidance behavior along migration routes [3, 4]. Using the annual avian collision mortality estimate of 200-500 million, it is estimated that wind turbines constitute 0.01 percent to 0.02 percent of the avian collision

fatalities[5] but these numbers could rise due the increasing construction of wind farms. While collisions are a direct cause of bird mortality caused by wind farms, the indirect mortality of birds due to an alteration in their flight patterns has yet to be investigated.

Current methods used for tracking bird migration involve either teams of human observers stationed at observation points along the predicted migration route[6] or tagging individual birds with a GPS receiver and data transmitter[7, 6]. The human observers are able to provide a count of bird species, thus giving a big-picture view of migration, and GPS data gives a detailed view of the migration of a single bird. Cine-theodolites are telescopic surveying cameras that have been used to enable measurements of bird track and speed, but these are expensive and cumbersome[8]. Vision has been applied successfully to many short-distance tracking problems. The application of computer vision for observing flight behavior at large distances is, however, a relatively unexplored concept.

An autonomous system to actively monitor the flight paths of raptors can add more insight to the available information without incurring the cost associated with having human observers and expensive equipment. This thesis describes a vision-based system for autonomously tracking birds as they fly past several observation points along the migratory route. The goal is to obtain enough information in the form of positions and velocities of individual raptors to facilitate a study of migratory routes of various raptor species. In addition to migration studies, such a system can be used to examine changes in flight patterns caused by obstructions such as wind turbines.

Observing birds from long distances calls for a set of sensors that is spatially distributed in a symmetric configuration to minimize the Dilution of Precision in any one direction. The implementation of a system that can incorporate a widespread distribution of sensors can be made more feasible by using more than one processor. A system with more than one processor would also be computationally efficient and better suited for real-time applications. Maintaining track at only one processor can lead to complete failure in tracking should a fault in the system occur. Loss of communication or processor failure would be less detrimental to the study should track be maintained by more than one processor. A Distributed Estimation system is therefore proposed for the bird tracking problem to meet the

requirements stated above.

1.2 Overview of the Bird Tracking System

Tracking from long distances using low-resolution and noisy measurement is a difficult problem prone to significant uncertainty and Dilution of Precision(DOP). The measurement model, which involves computing bearings using trigonometry, makes the estimation problem a non-linear one. The problem of non-linear estimation can be tackled by using one or more of the textbook non-linear Kalman filters. DOP may be lowered by using a set of sensors that are spatially spread out and arranged symmetrically, so that ambiguities in various directions may cancel each other out. The limitations provided by the terrain of the geographic site and the physical constraints of the hardware can be faced by implementing a Distributed System. The Distributed System consists of independent tracking stations each computing independent estimates. Local estimates can be fused to provide the resulting higher priority state estimate which would be the best estimate at that time interval. The fusion algorithm must account for the shared process noise among all local stations in order to avoid overconfidence in the state estimate.

Track needs to be initiated when a bird is seen at any of the local stations for the first time. Since no prior information is available to the tracking system regarding the state of the bird, the Particle Filter may be used to compute an initial estimate and covariance of the bird, that are Gaussian enough to be used as initial estimates for Kalman Filter based tracking. A distribution of particles that represent all possible states of the bird form the basis of the particle filter. The measurements from the cameras that view the bird are then used to provide a weight for each particle based on how closely the proposed measurement for that particle matches the true measurement to the bird in view. The weighted mean and covariance of these particles may be used as the initial estimate and associated covariance for the state of the newly seen bird. Once track is initiated at a particular station, track is maintained by performing motion and measurement updates using the Sigma Point Kalman Filter (SP-KF) to compute independent estimates at each time step. Should a previously seen bird come into view at another station, track would be initiated with the best available estimate. Consequent estimates may be obtained

by fusing all the available local estimates of the bird.

The assumption of data association is inherent in the Kalman filter although the sensors do not perform data association, they only provide a set of measurements, the association of the measurement set to the birds being tracked has to be computed explicitly. The data association has to be performed between pairs of cameras to ensure that the pair of bearing measurements from the stereo pair at each station correspond to the same bird. Data association also has to be performed from frame to frame so that a correspondence is maintained between bearing measurements obtained from one frame to the next. The camera-to-camera correspondence of measurements can be computed by checking the epipolar constraint between the stereo pair. If the epipolar constraint is satisfied, the measurement from both cameras belongs to the same bird. The measurements obtained from one camera can therefore be reordered to correspond with the measurements to birds seen by its stereo pair. Similarly, the gated Mahalanobis distance between the estimated state vector in the present and previous frame, can be used to perform frame to frame data association. The combination with the minimum distance provides the correspondence from one frame to the next. It is important to ensure that each set of bearings obtained in the current frame corresponds to only one other set in order to avoid the double copy of one bird and the loss of another from the track.

1.3   Previous Related Work

1.3.1   Bird Observation Methods

The most popular method for studying hawk migration has been counting of birds by human observers, followed by trapping and banding [8]. Counting migrating birds is the most fundamental study method and has been successfully employed as a bird observation method. Counting relies heavily on volunteers who have to invest long hours to be able to spot some of the rarer species. Data obtained from manual counts is susceptible to bias based on the geographic location of the observation site and error due to the limitations of the visual capacity of human beings. Also, counting only provides information about the species population from which

flight patterns can only be vaguely inferred. Tagging gives additional information about geographic origins and approximate flight paths but it comes with its own set of biases based on the age and sex of birds that are captured more easily than others. The small sample size from tagging makes the data less conclusive and the low recapture rates of banded birds makes it impossible to reliably answer important questions. Using markers that can be detected from a distance instead of tags will allow monitoring without recapturing and increase the amount of data collected. Radiotelemetry is a method that involves attaching a powered radio transmitter to individual birds in a species and following the course of the birds flight by keeping track of the signal transmitted. Tracking birds using radar had been a popular and effective way to study bird migration. Radiotelemetry and radar have provided the best data for the study of flight patterns but they can be prohibitively expensive[8].

In recent times, vision techniques have been proposed by Andrea Cavagna for modeling the flight and flocking patterns of starlings [9] and by Tomassi Crudeli to detect and vectorially track the movement of birds flying around airports [10]. Cavagna and his team have used the epipolar constraints of a flock of starlings viewed by a pair of stereo cameras to reconstruct the 3D positions of individual starlings by employing existing image processing and pattern recognition techniques. The computation of position is performed independently in every time interval and there is no association in the position of the bird computed from one frame to the next. This is a static procedure and it does not maintain the successive track of individual birds over a course of time. The vectorial tracking method is proposed by Crudeli for tracking birds on airports, that may be a potential threat to aircraft. Crudeli's method also involves using epipolar constraints to determine a 3D position for an individual bird. The position data is further post processed to trace a flight path for the bird. This method is used to detect birds at a close range by geometrically computing the position of the bird anew in each frame. The accuracy of the method and it's performance in tracking multiple birds has not been documented.

In the case of observing the effect of wind farms on the mortality of migrating hawks, periodic mortality surveys are carried out by teams of observers at the site specified. The mortality rate is observed by counting carcasses of birds at periodic

intervals. The effect of scavenging by other predators also has to be accounted for in order to avoid the underestimation of mortality rates. The effects of location, weather and flight behavior on collision possibilities have previously been analyzed using generalized linear modelling[4].

1.3.2 Vision Based Tracking

Cameras are inexpensive sensors that impart a wealth of information pertaining to color, prominent features, position and motion of filmed objects. Stereo camera systems also allow triangulation to add depth information and provide measurements from various viewing angles to significantly lower uncertainty about the state of the subject under observation. Stereo cameras have been used by Cavgna and Crudeli for position estimation of birds using epipolar geometry. Vision data from a stereo camera system, has been used by Muñoz-Salinas and Auirre in a Kalman Filter based application to track moving people[11]. Color is an invaluable tool for the identification of subjects in an image and color histograms are unique markers for objects to be tracked. The color information associated with each subject being tracked has been used by Salinas and Auirre, as well as Bahadori and Iocchi, to perform data association and maintain the identities of people being tracked[11, 12]. Color histogram based tracking has been made popular by Zivkovic and Krose [13], but it is computationally expensive to extract color information in every frame. Using a Kalman filter for frame to frame tracking and color information over longer time intervals, to maintain data association, is more viable for real-time applications. It should be noted that human tracking is carried out at far closer distances than bird tracking and the vision information available in the former case is therefore more enriched and accurate.

1.3.3 Non-linear Estimation

The Kalman Filter is the optimal filter for linear estimation. Since the measurement model for the proposed system is non-linear, the assumption that the estimates remain Gaussian does not hold, causing the Kalman Filter to fail. The problem of non-linear estimation is not a recent one, since most physical systems have non-linear properties. The Kalman Filter itself can be modified to accom-

modate non-linear system equations. By linearizing the system equations, the non-linear system can be converted into a linear system on which the Kalman Filter would be able to operate. The Extended Kalman Filter (EKF) works on this principle. The system equations are linearized about an initial estimate using a first order Taylor series expansion. The removal of higher order terms and use of an approximate initial estimate have a negative effect on the optimality of the linearized Kalman Filter or the EKF . The EKF is also computationally difficult to implement and can diverge if the initial estimate or the linearized system equations are inaccurate. Despite its drawbacks, the EKF has been the tracking system of choice in several navigation systems and GPS [14].

The Sigma Point Kalman Filter (SP-KF), also known as the Unscented Kalman Filter (UKF), uses a set of deterministic points with a Gaussian distribution about the current best estimate, to model the estimate and its statistics [15]. This set of points, called Sigma Points, can be propagated through the non-linear system equations instead of a single value. After propagation through the non-linear equations, the mean estimate and the covariance associated with it are computed from the distribution of these points. The square-root implementation of the SP-KF allows faster computation and ensures that the covariance is always positive definite [16]. The UKF has been used for pose estimation in the Model-based 3D tracking of an articulated hand [17].

The non-linear estimators introduced so far all assume that the estimate and its covariance follow a Gaussian trend. This assumption is not always true, especially if no prior information is available. The Particle Filter is another Bayesian Filter that can operate without making any assumptions about the probability distribution function of the model under observation [18]. The Particle Filter computes the estimate and its covariance by carrying out a weighted resampling of a set of points that simulate all possible values of the state. The weights are allotted proportional to the resemblance of the point, or particle, to the true state, as inferred from the measurements available. The particle filter has performed successfully in several positioning, navigation and tracking applications [19]. The accuracy of the Particle Filter is dependent on how closely the particle selected matches the true state. A large set of particles therefore required to amply cover the space of possible states. This makes the particle filter computationally unwieldy and limits

its operational capability, especially in real-time applications.

1.3.4 Distributed Systems

Distributed systems have received increasing attention due to the several advantages that they offer over centralized systems. Having multiple processors lowers the computational load and the dependence on any one node. A variety of measurements can be incorporated into the tracking process since each processor has the provision of having its own measurement model. A distributed system can also cover a larger area compared to centralized system since each sensor need not be connected to the central processor. The fusion of data in distributed systems has been an active area of research. The process noise in a distributed system is shared and fusion algorithms have been developed that account for this while computing a fused estimate. Distributed systems may be implemented in various structures or hierarchies based on the application. The textbook by Bar-Shalom and Li provides a detailed documentation of of theory and implementation of a variety of Distributed Sensor Networks (DSN) for tracking multiple targets using multiple sensors[20]. Tracking of human subjects and mobile robots in an indoor smart environment using has been achieved by Karuppiah and Zhu through a distributed vision system with heterogenous sensors of various processing rates, synchronized and fused to achieve real-time tracking [21].

1.4 Contributions

The following project has built upon previous tracking methods to simulate the outdoor, long-distance tracking of raptors using stereo camera systems and distributed processors, implemented using various forms of the Kalman Filter. The main contributions of this thesis are described in the following section.

1.4.1 A novel bird observation technique

A continuous and autonomous method has been proposed that can keep track of the position and velocity of the birds in view. The system, consisting of a set of off-the-shelf cameras and processors, does not require a great deal of fiscal or labor input.

Stereo-cameras can provide depth information based on epipolar constraints, and allow 3D estimation from 2D image information. The distribution of cameras can be specified based on the geography of the observation site. Bird dynamics and the measurement model are simulated based on expected behavior and physical constraints. The results of the proposed system, on simulation, show that a fairly accurate track of individual birds is maintained even from large distances.

1.4.2   Application based estimator designs

Once the bird dynamics and measurement models are constructed mathematically and simulated, the estimation process can begin, which involves computing an estimate of the dynamic state using the available measurements. The choice of states is a trade-off between the complexity of the estimation process and the information required to form a complete picture of the migratory route. The state vector chosen consists of the 3D position and velocity components. Fundamental vision techniques and trigonometry can be used to obtain the bearing to any object in view of a camera. The measurements used in the bird tracking problem are, therefore, bearings to the bird from each of the cameras in the system. Since the measurement model used to compute these bearings contains trigonometric functions, the estimation process becomes non-linear. The variations of the Kalman Filter for non-linear estimation were all considered and the Square Root form of the Unscented Kalman Filter was chosen. The Square-Root UKF was chosen due to its ability to generate consistent estimates without divergence and its computational efficiency. The prediction and correction equations were derived based on the bird dynamics and measurement model, respectively. The UKF requires an initial estimate and covariance, having a Gaussian distribution, in order to carry out the subsequent estimation procedure. The only information available when the bird first comes into view is a set of bearings from all the cameras that view it. Several geometric triangulation approaches were tested before the Particle Filter was employed. A specific initialization process was designed to compute an initial estimate that led to satisfactory results once fed to the UKF . A set of particles, having a Gaussian distribution, are created in a solid angle about a bearing and weighted proportional to the similarity between the expected bearing mea-

surements to it and the available bearings to the true position of the bird. The weighted mean and covariance are computed to obtain an initial estimate for the 3D position of the bird and its covariance. It is found that using arbitrary velocity components based on the expected velocity of the bird is sufficient for initialization purposes, since the deviation of velocity from its expected values is much lesser than that of position. The Particle filter based initialization process, although heuristically designed, gave better initial estimates than plain trigonometry. The results obtained from this process, are stable and Gaussian in nature and allow the UKF to compute fairly accurate estimates, without causing divergence. The performance of estimators designed is tested for multiple different tracking runs and satisfactory results are obtained.

1.4.3   Distributed implementation

A Distributed Hierarchical system is designed such that each camera in the system sends its measurements to a local processor that computes an independent local estimate. All local estimates are communicated to a central processor via wireless communication and fused to compute a higher priority global estimate. The fusion computation accounts for the shared process noise by subtracting the information that has been added multiple times from the covariance to ensure that the accuracy of the estimate remains bounded by the noise present in the system. Once a fused estimate is computed, it is regarded as the current best estimate and is transmitted back to all the local processors. This step is important since it puts all the local estimators on the same level of certainty at each time step and averts the possibility of a drift of local estimates from each other. The system designed as described is tested against the conventional centralized implementation and results are found to be identical, as expected, since the information available to both systems is the same. The distributed implementation of the system, however, has the added advantages of being easier to implement physically, more computationally efficient, robust and versatile to a variety of measurements.

1.4.4   Performance Verification: Simulation

A Monte-Carlo simulation consisting of a number of varying flight paths is run to test various aspects of the estimation process. The error in position between the true and initial estimates of position are compared to the condition number of the initial covariance matrix. It is found that even for initial covariances with a relatively high Dilution of Precision, the error in the estimate remains reasonable and bounded. The mean squared error in the estimate for all estimates, is compared to the square root of the trace of the covariance of the estimate as computed by the UKF and they are found to correspond with each other. Hence proving that the estimated error is found to match the true error. The performance of the distributed implementation is compared to that of the centralized version and both results obtained are identical as expected. This indicates that the fusion technique employed is representative of the interaction between estimators and accounts for the process noise shared among them. The advantage of a distributed system over a centralized one can therefore be exploited at no loss to the quality of the tracking system's performance.

1.5   Reader's Guide

The chapters that follow can be summarized as follows:

- **Chapter 2: The Bird Tracking Problem** describes the tracking problem mathematically and proposes the components of states to be estimated. Mathematical models are derived to describe the dynamics of the birds and the procurement of bearing measurements from the view of the bird in the camera. Aspects of non-linear estimation and distributed systems are introduced.

- **Chapter 3: Tracking System Design** defines the tasks to be accomplished by the estimator, namely, track initiation, estimation and data association. It goes on the present the mathematical implementation of the aforementioned based on the structure of the system, the quantities to be estimates, the type of estimator and the hierarchy of the processors. The flow of data within the

system is summarized to give a quick description of the implementation of the tracker.

- **Chapter 4: Bird Tracking Simulation Results** begins with a description of the simulation setup designed to test the performance limits of the system. The various parts of the estimation process, i.e, track initiation, tracking performance and data association are tested and Monte-Carlo results are presented with corresponding inferences.

- **Chapter 5: Conclusion** discusses the scope of the research presented and explores areas of future work

Chapter 2

The Bird Tracking Problem

THE FOLLOWING CHAPTER defines the bird tracking problem.
The major topics discussed are:

1. *Problem Statement*: The setup of the tracking problem is described and appropriate states are chosen for the state space model. A spatially distributed geometry is proposed for sensor locations in order to lower Dilution of Precision.

2. *Sensor and System Model*: A mathematical model is proposed to simulate the bird kinematics, the parameters of which form the system under observation. A sensor model is proposed to emulate the working of the sensors, a set of stereo cameras. The measurement of bearings to birds in flight is simulated by this model

3. *Non-linear and Distributed Estimation*: Popular methods in non-linear estimation are discussed, to address the non-linearities in the measurement model. Distributed Estimation is introduced along with the advantages it has over conventional estimation, given the nature of the bird tracking problem.

The choice of states for estimation is the first step in formulating a mathematical tracking procedure. The states chosen should be able to depict all important factors in the system and track them with reasonable computational complexity. For an observation problem like this one, knowing the position and velocity of the

bird in one fixed coordinate system is sufficient for tracing out its migration route. The bird kinematics proposed are linear and without acceleration, to depict the flight of a raptor across the horizon with reasonable accuracy. Computing position from bearing measurements employs trigonometric functions, which leads to a non-linear estimation problem. Fortunately, there are several methods that have been successfully implemented for non-linear estimation, some of which are discussed in Section 2.4. Observing small objects from great distances causes uncertainty in the estimates due to Dilution of Precision. Having well spread out sensors can counter DOP but connecting faraway sensors to one processor can be difficult to construct physically. This is the motivation behind using a Distributed Estimation system as proposed in Section 2.4.3.

2.1 Problem Statement

The problem considered here is the observation of migrating raptors in order to determine their flight path as they pass the observation stations. The sensors available are sets of cameras placed along a ridge on the migratory route. Bearings are obtained from all cameras at which a bird is in view. For a single bird the vector of states to be estimated includes components of position x^o, y^o and z^o and velocity $\dot{x}^o$, $\dot{y}^o$ and $\dot{z}^o$ expressed in the North East Down (NED) frame:

$$\mathbf{x}_{b,i}^o = \left[\begin{array}{cccccc} x_{b,i}^o & y_{b,i}^o & z_{b,i}^o & \dot{x}_{b,i}^o & \dot{y}_{b,i}^o & \dot{z}_{b,i}^o \end{array} \right]^T \tag{2.1}$$

The schematic of the estimation problem is shown in Figure 2.1.

The flight path of a bird, b, is shown. At any instant of time, i, the state of the bird, $\mathbf{x}_{b,i}^o$, is determined. The coordinates $(x_o y_o z_o)$ represent position in global NED coordinate system. The system is scalable at two levels. At the station level, a set of two or more cameras can be used to compute a local estimates. Further, at the global level, local estimates from any number of distributed stations can be used to compute fused global estimates of birds in view at these stations. Every camera in the system is considered to have its own local coordinate system, with the x axis pointing outwards from the lens along the optical axis of the camera and the y and z determined by the pan or tilt of the camera about its origin. Each
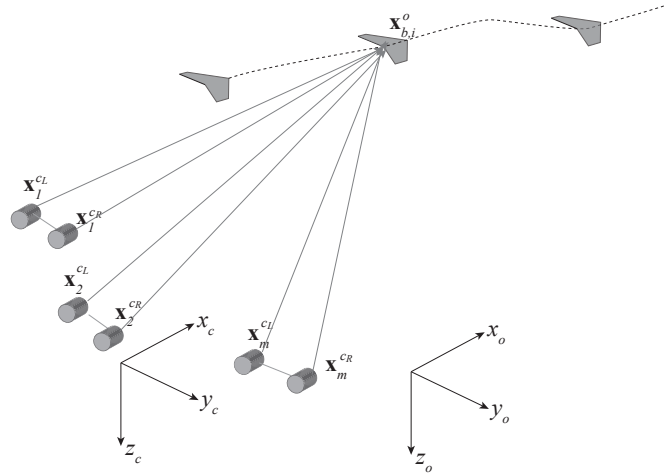
Figure 2.1. Schematic of the bird tracking problem.

camera has its own origin and rotation angles. The coordinates $(x_c y_c z_c)$ represent the position of the bird as seen in the local coordinates of the camera in which it is viewed. Available measurements are bearings obtained from the array of cameras placed at known positions and orientation.

Computing position estimates from bearing measurements involves trigonometric functions. The tracking problem is therefore a non-linear one. The Kalman Filter, which is the optimal linear filter, is not applicable to this problem. A tracking method that can produce fairly accurate estimates despite the non-linearity of the system equations must be employed to achieve the results required. In addition to the non-linear nature of the system, a challenge is posed by the high degree of uncertainty inherent in tracking small objects from large distances, which leads to Dilution of Precision. Having symmetrically spread out sensors over large distances can counter this problem since the ambiguity in opposite directions cancel out. Implementation details, however, limit the the distance between cameras at a station, or the baseline, since it is difficult to transmit data to a central station over a large baseline due to wiring constraints.
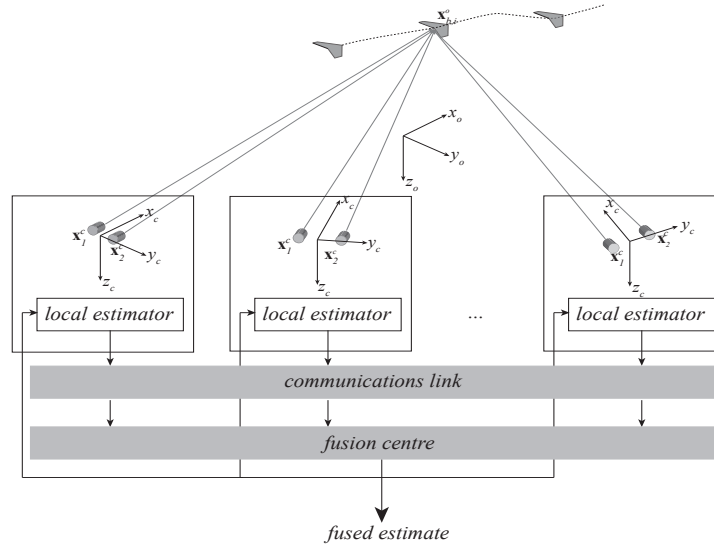
Figure 2.2. Schematic of the distributed implementation of the bird tracking problem.

2.2 A System for Tracking Migrating Raptors

In order to overcome the problem of Dilution Of Precision (DOP) due to short baselines between cameras, several independent stereo camera systems can be planted along the ridge at longer distances in a geometry that reduces DOP . The requirement for a spatially spread out and robust system has been met by designing a Distributed System which has several processors independently tracking the birds and a central processing unit that fuses all available estimates to compute a more accurate global estimate of the states. Assimilating measurements from various sensors, requires a tracking system where the number of available measurements can vary. Using multiple processors will not only allow a spatially distributed geometry to counter DOP but also make the system more robust to sensor or communication drop outs, since track would be maintained at each processor. Estimates may be computed independently at each node to be fused into one global estimate that can be used as the best estimate for a particular time interval, as shown in Figure 2.2. The fusing algorithm must account for the process noise due to the shared kinematic model at the processors in order to avoid overconfidence in the estimated state.

In order to compute estimates in a system consisting of non-linear equations,

a tracking system that can counter non-linearity needs to be used. Variations of the Kalman filter, like the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF) have been used successfully in non-linear tracking problems in the past. Appropriate filters need to be employed at various stages of the tracking problem depending on the nature of the information available. The Unscented Kalman Filter (UKF) works on the principle of propagating a set of particles through a non-linear system of equations instead of a single random variable, to get good estimates despite non-linear nature of the system. The particles used by the UKF are obtained deterministically and have a Gaussian distribution. The UKF is therefore a Gaussian filter, based on the assumption that the particles distributed through it maintain an approximately Gaussian distribution even through non-linear transformations. Hence, in order to use the UKF for tracking, a Gaussian initial estimate is required. The Particle filter, a Bayesian filter that makes no assumption about the distribution of the state, may be used to compute an initial estimate of the bird state and the covariance associated with it. The estimate computed by the Particle filter may be used to initialize UKF tracking.

The assumption of data association is inherent in the aforementioned tracking systems. However, the measurements obtained from camera-to-camera do not necessarily correspond to the same bird, should more than one bird be in view. Similarly, measurements obtained from one frame to the next need not correspond each other. In order to ensure the smooth functioning of the tracking systems it is important to know which measurement corresponds to which bird and use them in tracking accordingly. A data association procedure is required to reorder the bearing measurements from camera-to-camera and frame-to-frame to ensure that a correspondence is maintained between each bird and the measurement associated with it.

2.3 Mathematical Model Formulation

2.3.1 Bird Kinematics

Although the flight speed of a raptor is accelerated noticeably during circling flight or a dive, it remains fairly constant along a migratory route [8].A constant velocity

model is therefore used to model bird flight, assuming a random walk behavior of minor acceleration, which is approximated in the process noise.

The choice of states results in a linear model for bird kinematics:

$$\dot{\mathbf{x}}_{b,i}^{o} = \mathbf{A}\mathbf{x}_{b,i}^{o} + \mathbf{B}\mathbf{v} \tag{2.2}$$

where

$$\mathbf{A} = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} \tag{2.3}$$

$$\mathbf{B} = \begin{bmatrix} \mathbf{0} \\ \mathbf{I} \end{bmatrix} \tag{2.4}$$

and $\mathbf{I}$ is the 3×3 identity matrix and $\mathbf{v}$ is zero-mean Gaussian random noise.

2.3.2 Measurement Model

Rather than using direct stereo vision techniques for computing range to a target (i.e. computing range based on disparity between the left and right cameras), the bearing from each camera to every bird is computed and treated as an independent measurement. The bearings obtained by the cameras at a station are fused using a Sigma Point Kalman filter. This method has the advantage of being easily scalable to adding more measurements and adaptable to the number of cameras at the station in which a bird is in view.

A pinhole camera model defines the projection of a vector onto the image plane as

$$\boldsymbol{\gamma} = \frac{f}{x^c} \begin{bmatrix} y^c \\ z^c \end{bmatrix} \tag{2.5}$$

where f is the focal length and $\mathbf{x}^c = \begin{bmatrix} x^c & y^c & z^c \end{bmatrix}^T$ is the vector expressed in the camera frame. The focal length f can be normalized without loss of generality.

The orientation of the camera frame for camera m, C_m ,with respect to the inertial frame O is assumed to be known. Each camera has a known pan, ψ, and tilt, θ. Rolling the camera about its axis does not add any more information to the scene in view. It is therefore assumed that there is no roll in any of the

cameras. The matrix, **T**, that transforms the universal coordinate frame to camera coordinates is given by as:

$$\mathbf{T} = \mathbf{T}_\theta \mathbf{T}_\psi \tag{2.6}$$

where $\mathbf{T}_\theta$ and $\mathbf{T}_\psi$ are rotation matrices

$$\mathbf{T}_\theta = \begin{bmatrix} \cos\theta & 0 & -\sin\theta \\ 0 & 1 & 0 \\ \sin\theta & 0 & \cos\theta \end{bmatrix} \tag{2.7}$$

$$\mathbf{T}_\psi = \begin{bmatrix} \cos\psi & \sin\psi & 0 \\ -\sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{2.8}$$

and

$$\mathbf{T} = \begin{bmatrix} \cos\theta\cos\psi & \cos\theta\sin\psi & -\sin\theta \\ -\sin\psi & \cos\psi & 0 \\ \sin\theta\cos\psi & \sin\theta\sin\psi & \cos\theta \end{bmatrix} \tag{2.9}$$

Depending on its orientation, each camera has a rotation matrix, $\mathbf{T}_m$, computed as shown in Equation 2.9. Each camera is assumed to have its optical axis aligned with the camera frame's $\hat{\mathbf{x}}^c$ axis and is offset from the origin of the camera in the station frame by a distance vector $\Delta\mathbf{x}_m^c = \begin{bmatrix} \Delta x_m^c & \Delta y_m^c & \Delta z_m^c \end{bmatrix}^T$. A bearing measurement to the ith bird at camera m is therefore

$$\boldsymbol{\gamma}_{m,i} = \frac{1}{x_{m,i}^c} \begin{bmatrix} y_{m,i}^c \\ z_{m,i}^c \end{bmatrix} \tag{2.10}$$

where

$$\begin{bmatrix} x_{m,i}^c \\ y_{m,i}^c \\ z_{m,i}^c \end{bmatrix} = \mathbf{T}_m \begin{bmatrix} x_i^o - x_o \\ y_i^o - y_o \\ z_i^o - z_o \end{bmatrix} + \begin{bmatrix} \Delta x_m^c \\ \Delta y_m^c \\ \Delta z_m^c \end{bmatrix} \tag{2.11}$$

The measurement vector **z** is formed by concatenating bearings from each of

the M cameras in the array:

$$\mathbf{z} = \left[\begin{array}{cccc} \boldsymbol{\gamma}_1 & \boldsymbol{\gamma}_2 & \cdots & \boldsymbol{\gamma}_M \end{array}\right]^T \qquad (2.12)$$

2.4   Non-linear and Distributed Systems

The mathematical model described in the previous section shows that acquiring state estimates from the measurements is a non-linear problem due to the trigono-metric functions involved. State estimation in linear systems is considered to be a solved problem since the invention of the Kalman Filter by Rudolph E. Kalman in 1960 [22]. The Kalman Filter is the optimal estimator for a linear system. The assumption of Gaussian-ness has to be upheld through all functions in the system in order to maintain the optimality of the Kalman filter. For linear systems, this holds true, but non-linear systems do not remain Gaussian at all points. Using a linear filter for non-linear systems can lead to highly erroneous estimates or never reach convergence. It is possible to linearize the system equations before propa-gating them through the filter. This is the rationale behind the Extended Kalman Filter (EKF), which approximates the system model with a first order Taylor Series approximation about the current best estimate. Using a linear model for a highly non-linear system can lead to severe biases and linearizing about an inaccurate estimate will result in equations that do not represent the system well. Moreover, the EKF is mathematically intensive and difficult to implement. The Sigma Point Kalman Filter (SP-KF), more affectionately known as the Unscented Kalman Filter (UKF), does away with the linearization procedure by computing an estimate for a set of points that mimic the probability distribution of the states to be estimated [15]. The Particle Filter also uses the principle of estimating states for several points, or particles, but these particles do not necessarily satisfy the Probability Distribution Function (PDF) of the state to be estimated. Both the UKF and the Particle Filter have been applied to the bird tracking problem, depending on the information available.

2.4.1   Particle Filter

The Particle Filter models all possible states of a system by a set of particles. The number of possible states increase with the number of particles, therefore the accuracy of the state estimate increases with the number of particles used. The Particle Filter does not make any assumptions about the probability distribution of the state. It yields good results for a non linear system where the probability distribution of the states can not be predicted. Initializing the particle distribution based on the first measurement greatly reduces the number of particles and prevents outlier estimates. Like the conventional Kalman Filter, the Particle Filter also has a prediction and a correction step. The prediction consists of propagating all the particles through the motion model to predict the state of each particle at the next time step. The correction step involves the resampling of predicted particles states based on measurements of the true state at that time step. The key ingredients for the successful operation of the Particle Filter is the resampling steps. The measurements available from the sensors, for the true position, are compared to those obtained by the measurement model, for each particle. The particles are weighted in proportion to how close the measurements for the particle are to the the true measurements available for the states. High weights are allotted to particles that match measurements closely and low weights to those that do not. Using an exponential weighting function will create more disparity in weighting than a linear function. Resampling involves recreating the existing set of particles by drawing particles from the set multiple times, giving priority to particles with high weight. This results in a new set of particles that has multiple copies of highly weighted particles and fewer versions of lower weighted particles. The probability distribution of the resampled set should represent that of the true set more closely. However, this is not always the case. If a sufficient number of particles is not used, the particle with the highest weight could be far from the true state but still be resampled several times, leading to a bad estimate. This is known as the particle deprivation problem. The random nature of resampling can lead to far-away particles being sampled several times and frequent resampling leads to a low variance estimate which is far from the true state. Resampling methods like low variance sampling, ensure that diversity is maintained in the particles and the possibility of discarding a more accurate estimate is lowered. Mathematical

derivations of the Particle Filter, its sources of error and means to improve its performance are listed in several textbooks [23, 24].

2.4.2 Unscented Kalman Filter

The Unscented Kalman Filter (UKF), like the Particle Filter, employs the propagation of particles through the system in order to deal with its non-linearities. However, unlike the Particle Filter, the particles used by the UKF are obtained deterministically and not randomly because the UKF is based on the assumption that the particles distributed through it have a Gaussian distribution. For an n state estimation, 2n+1 particles, or Sigma Points, are sampled symmetrically about the mean. These Sigma Points have a normal distribution with mean, $\bar{\mathbf{x}}$, and covariance, $\mathbf{P}$, which are the best available estimate and the covariance associated with it respectively. The set of sigma points is given by:

$$\mathbf{X} = \left[\begin{array}{ccc} \bar{\mathbf{x}} & \bar{\mathbf{x}} + \eta\sqrt{\mathbf{P}} & \bar{\mathbf{x}} - \eta\sqrt{\mathbf{P}} \end{array} \right] \tag{2.13}$$

where η is a scale factor that determines the spread of the Sigma Points about the mean.

Although the system is non linear and Gaussian-ness may not be maintained, the assumption of the Sigma points having a Gaussian distribution is made and their mean and covariance is computed to represent the state estimate. The Sigma Points are propagated through the prediction and correction steps of the Kalman Filter and the mean and covariance of these points give the state estimate, $\hat{\mathbf{x}}$, and the associated covariance, $\mathbf{P}$.

2.4.3 Distributed Estimation

A set of cooperative stations that take independent measurements and compute separate estimates form the Distributed Estimation network. In a non-hierarchical system, the estimates computed by each station are treated equally and independently, leading to several estimates of the same state. Fusing these local estimates to form one, global, higher priority estimate of the state is the principle of the Distributed Hierarchical Estimation (DHE) system. Fusing algorithms must ac-

count for the process noise being shared by all the stations which results in a correlated estimate error. The compilation by Bar-Shalom [20] describes several Distributed Estimation implementations and algorithms for optimal fusion of multiple estimates. Distributed systems have received increasing attention due to the several advantages that they offer over centralized systems. Tracking the target simultaneously at several locations lowers the computational dependence at any one node. This makes the system more robust and the complete loss of track due to the failure of the central processor is prevented. The accuracy in tracking the states only deteriorates should any of the several processors fail. Track is also maintained at each of the independent stations in the event of the failure of the central fusing unit. The computational load is shared by several processors, which cuts computation time and makes the system better suited for real-time applications. Distributed systems are scalable to the number of measurements available and since independent estimates are computed, the option of using different types of sensors and measurements also exists. For a geographically spread out tracking problem like the one in question, the sensors need to be well distributed in space. Using a distributed implementation increases flexibility in sensor geometry and the communication system between sensors can used to transmit estimates instead of measurements for a robust distributed estimation system.

2.5   Summary: The Bird Tracking Problem

The bird tracking problem is defined mathematically in Section 2.1. Estimating the position and velocity of each bird, enables the documentation of migratory routes, and the states for the estimation problem are chosen accordingly. Observing birds from a long distance increases Dilution of Precision. A spatially spread out system would be able to overcome this problem but it would be difficult to connect faraway sensors to the same hub. The number of measurements available depends on the number of cameras in which the bird is viewed, and this will easily vary as the sensors increase in number and get further away from each other. The system proposed should be able to utilize any number of available measurements. The seasonal nature of the bird tracking problem makes it imperative to keep continuous track. Loss of track will affect the reliability of the study and can be

difficult to recover from. The need for a system that is adaptable to changing levels of information, while being robust and computationally efficient, motivates the implementation of multiple, distributed processors.

Since this is a theoretical project, the dynamics of birds and the measurements obtained need to be modeled mathematically. Mathematical models are defined in Section 2.3. The dynamics of birds as defined are linear and acceleration is modeled as random process noise. The measurement model computes bearings to the bird position as viewed in the coordinate system of the camera. The trigonometric identities present in the measurement model introduce non-linearity into this tracking problem.

The problem of non-linear estimation has been address by several variations of the optimal linear Kalman Filter. The Particle Filter and Unscented Kalman Filter are described in Sections 2.4.1 and 2.4.2. The Particle Filter can be used to compute an estimate when there is no prior knowledge. Multiple versions of the state estimate are weighted and resampled with every available set of measurements to compute an estimate that is most closely matches the values inferred by the measurement. The UKF is a deterministic approach that models a symmetric distribution about the current best estimate. The estimated state and covariance are functions this distribution, which is able to maintain its configuration through non-linear transforms. Both the particle filter and the UKF are applied to various aspects of the bird tracking problem. The implementation of both is described in Chapter 3 and the results obtained are documented in Chapter 4.

Distributed Hierarchical Estimation is introduced in Section 2.4.3 to address the implementation details that a centralized system would not be able to satisfy. A distributed system, tracks with the same degree of accuracy as the tried and tested centralized system, but it is more robust, computationally efficient and geometrically flexible compared to it. It is important to keep in mind that nodal estimates are not completely independent of each other due to the common process noise and to account for this while fusing the estimates. The results obtained by Distributed Estimation are shown in Chapter 4 and compared to those obtained by Centralized Estimation.

Chapter 3

Tracking System Design

THE TECHNIQUES TO ACHIEVE the task defined in the previous chapter are proposed in this chapter. The tracking problem can be divided loosely into three sub-tasks, listed as follows:

1. Track Initiation

2. Data Association

3. Estimation

The particle filter, introduced in Section 2.4.1, can be applied to the track initiation problem, which requires the computation of an initial estimate given no prior information. The specific implementation of the particle filter to achieve an initial estimate for the bird tracking problem is described in Section 3.1. Once an initial estimate and the covariance associated with it are obtained, the estimation process can be carried out by the deterministic and computationally cheaper Unscented Kalman Filter, which was introduced in Section 2.4.2. The UKF operates on the statistics of a set of deterministic state points that maintain a fairly Gaussian configuration even through non-linear transformations. The computational benefits of the UKF make it suitable for real time estimation. The need for a geometrically flexible and robust tracking system is met by the Distributed Hierarchical implementation of the the tracking system. As discussed in Section 2.4.3, Distributed Hierarchical Estimation involves the fusion of several local estimates to compute one higher priority global estimate. The UKF is employed for the computation of

local estimates, the implementation of which is described in Section 3.3.1. The fusion of local estimates is not a simple averaging procedure, and should address the shared process noise among local estimators. The fusion procedure and the relation between local and global estimates is described in Section 3.3.2. The results for the implementation of the tracking system as described in this chapter are listed in Chapter 4.

3.1   Track Initiation

Track initiation can be a thorny problem, especially when range data is uncertain (which is the case for short-baseline multiple camera systems). A closely related problem, feature initialization in Simultaneous Localization and Mapping (SLAM), has the same difficulties. Feature initialization in bearings-only SLAM is especially difficult, and has been the subject of a large amount of research. "Delayed approaches" collect several bearings over time and fuse them to compute an initial estimate of landmark position[25, 26, 27]. "Undelayed approaches" represent the conical probability distribution associated with a bearing measurement as a series of Gaussians which are then pruned as more measurements become available[28, 29, 30]. These are essentially multiple hypothesis filters. The main issue which these methods attempt to address is ensuring that the initial landmark position is "Gaussian" enough be incorporated into a Kalman filter (e.g. EKF or UKF) without causing stability problems.

Here we have used an undelayed approach based on the Particle Filter [18]. Since an undelayed approach is adopted, only one set of measurements is used and there is no time update. Initializing the state of the bird based on the triangulation of available bearings is a nonlinear problem and may not result in a sufficiently Gaussian estimate. A set of N particles, representing possible target locations, can be processed by the Particle Filter to compute a Gaussian estimate of the initial position of the bird. The initial set of particles are simulated along the entire range, R_{min} to R_{max}, the first available azimuth, ξ , and elevation, θ to a bird entering the field of view. The 3D position, $\mathbf{x}_p$,of any one particle in this normal distribution is given as:

$$\mathbf{x}_p = \begin{bmatrix} r_p \cos(\theta_p)\cos(\xi_p) \\ r_p \cos(\theta_p)\sin(\xi_p) \\ r_p \sin(\theta_p) \end{bmatrix} \tag{3.1}$$

where

$$r_p = U(R_{min}, R_{max}) \tag{3.2}$$

$$\theta_p = N(\theta, v_m^2) \tag{3.3}$$

and

$$\xi_p = N(\xi, v_m^2) \tag{3.4}$$

v_m being the measurement noise of the camera from which the bearing is obtained.

The set of particles thus generated have a Gaussian distribution across the conic section of the solid angle formed by the deviations about the true bearing to the bird, on account of the measurement noise v_m. This is shown schematically in Figure 3.1.

For each of the N particles, the predicted measurement from the remaining, $M-1$, cameras is computed. The bearings used to form the initial probability distribution are not included to avoid the bias from counting it twice. $\mathbf{z}_p$ is given as follows:

$$\mathbf{z}_p = \begin{bmatrix} \boldsymbol{\gamma}_1 & \boldsymbol{\gamma}_2 & \cdots & \boldsymbol{\gamma}_{M-1} \end{bmatrix}^T \tag{3.5}$$

A weighting of the distribution can now be carried out based on how closely the measurement vector, $\mathbf{z}_p$, to each particle matches the actual measurement vector, $\mathbf{z}$, for the $M-1$ cameras. The weight of each particle, w_p, is inversely proportional to its exponential distance from the mean in the multivariate normal distribution of mean $\mathbf{z}$ and covariance $\boldsymbol{\Sigma}_m$. w_p is computed using the following equation:

$$w_p = \exp[-0.5\boldsymbol{\Delta}_z^T \boldsymbol{\Sigma}_m^{-1} \boldsymbol{\Delta}_z] \tag{3.6}$$
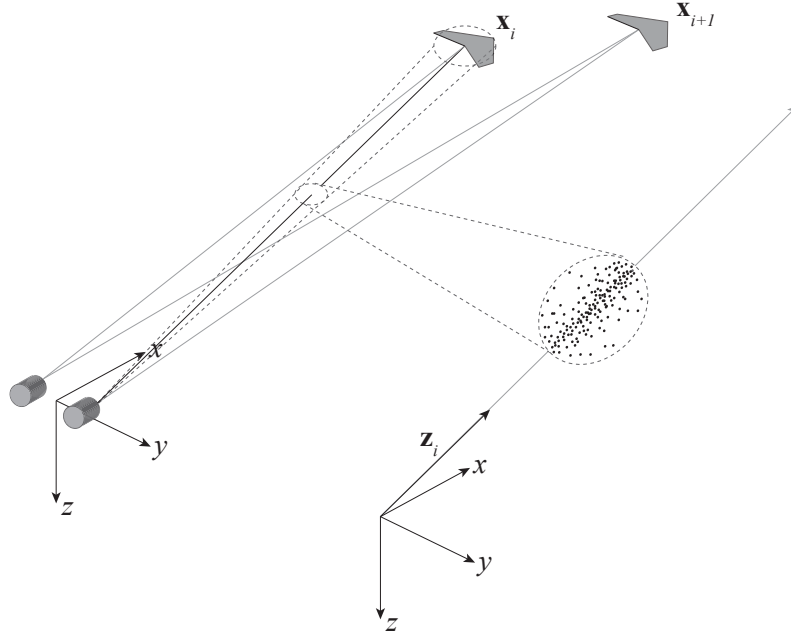
Figure 3.1. Track initiation. Bearings to a bird are treated as rays originating from camera frame origin to the bird. The uncertainty in the bearing measurement is treated as a zero-mean Gaussian, creating a probability cone. Each particle in the distribution has a weight associated with it, which is inversely proportional to the deviation of the bearing to that particle from the measured bearing to the bird. The bird's initial state is computed as the weighted mean of particles.

where

$$\boldsymbol{\Delta}_z = \mathbf{z} - \mathbf{z}_p \tag{3.7}$$

and

$$\boldsymbol{\Sigma}_m = v_m^2 \mathbf{I} \tag{3.8}$$

$\mathbf{I}$ being an $M - 1 \times M - 1$ identity matrix.

Having computed weights, w_p, to each particle, an estimate for the initial position, $\hat{\mathbf{x}}_{p_0}$ and the covariance, $\mathbf{P}_{p_0}$ associated with this estimate, may be computed. For this application, the weighted mean and weighted covariance of the particle distribution, as shown in Equations 3.9 and 3.10, are used for $\hat{\mathbf{x}}_{p_0}$ and $\mathbf{P}_{p_0}$ respec-

tively.

$$\hat{\mathbf{x}}_{p_0} = \sum w_n \mathbf{x}_p \tag{3.9}$$

$$\mathbf{P}_{p_0} = \Delta \mathbf{x}_p \text{diag}(w_n) \Delta \mathbf{x}_p^T \tag{3.10}$$

where

$$\Delta \mathbf{x}_p = \mathbf{x}_p - \hat{\mathbf{x}}_{p_0} \mathbf{1} \tag{3.11}$$

and w_n is the normalized form of the weights vector w_p.

In order to form a complete estimate of the initial state, $\hat{\mathbf{x}}_0$, and its covariance, $\mathbf{P}_0$, NED components of the bird's velocity also need to be estimated. Having adopted an undelayed approach for initialization, it is not possible to observe the dynamics of the bird. However, since the range of the velocity of the bird is a lot more limited than that of position, flight speeds are picked for the velocity components of the state vector based on documentation provided by Kerlinger[8], and the assumption that the bird is flying parallel to the ridge. The flight speeds of some species of raptors is presented in Table 3.1, based on the data published. Note that best glide is defined by the maximum lift to drag ratio achieved by the bird [8]. A reasonable covariance is also selected based on the expected variation in velocity components along the NED coordinate system. The estimated velocity vector and covariance matrix are concatenated with $\hat{\mathbf{x}}_{p_0}$ and $\mathbf{P}_{p_0}$ to obtain $\hat{\mathbf{x}}_0$ and $\mathbf{P}_0$.

Note that the track initialization as described above is only carried out when a bird is first viewed by any one of the cameras in the distributed system. If a bird is initialized on being viewed by one set of stations, consequent stations can initialize their track, once the same bird comes into view, with the fused global estimate transmitted to them.

3.2   Data Association

Data association can be a difficult issue in many tracking problems, especially when attempting to fuse bearing only data. Although the frequency of bird passage is

Table 3.1. Summary of Aerodynamic Performance of Raptors

Species	Air Speed at Best Glide (ms^{-1})	Sink Rate at Best Glide (ms^{-1})	Cruising Speed (ms^{-1})
Sharp-shinned Hawk	10.5	1.2	22.5
Broad-winged Hawk	11.6	1.1	24.2
Lanner Falcon	10-14	1.0	-
Red-Tailed Hawk	14.5	1.6	23.9
Osprey	11	0.9	24.9
Black Vulture	13.9	1.2	16.8
White-backed Vulture	13.5	1.1	16-20+
Andean Condor	NA	NA	15.0

low enough that in general we can expect only one bird to be in the field of view, we will address the problem of data association. In addition to allowing operation when multiple birds are in the field of view, it will also increased robustness to clutter.

The data association is preformed at both camera-to-camera and frame-to-frame levels. Data is associated between stereo pairs at each station by checking epipolar constraints between images seen in both cameras. If the epipolar constraint, given by Equation 3.12, is satisfied, the camera coordinates $\mathbf{x}_{c_R}$ and $\mathbf{x}_{c_L}$ correspond to the same bird.

$$[\mathbf{T}_L \mathbf{d}_c + \mathbf{T}_L \mathbf{T}_R \mathbf{x}_{c_R} - \mathbf{d}_c]' . \mathbf{d}_c \times \mathbf{x}_{c_L} = 0 \qquad (3.12)$$

$\mathbf{T}_L$ and $\mathbf{T}_R$ are the rotation matrices for the left and right cameras respectively and $\mathbf{d}_c$ is the 3D displacement between the stereo pair. For data association from frame to frame, bearings obtained at each station after camera-to-camera association, are compared to the bearings obtained in the previous frame and re-ordered at every time step so that the same order is maintained throughout the sequence. Association of corresponding camera coordinates between the actual and predicted measurements is based on the Mahalanobis distance between any two sets of bearings, $\mathbf{z}_i$ and $\mathbf{z}_j$, and is as follows.

$$d_{ij} = (\mathbf{z}_i - \mathbf{z}_j)^T \mathbf{P}_{jj}^{-1} (\mathbf{z}_i - \mathbf{z}_j) \qquad (3.13)$$

The matrix $\mathbf{P}_{jj}$ is an arbitrary covariance associated with the measurement noise.

The number of birds seen at any time and the order in which they are seen varies from station to station. This leads to a variation in the order in which local estimates are computed at each station. Further data association needs to be carried out before fusing the local state estimates that are transmitted to the fusion center to compute the global estimate. The local estimates obtained at each station are compared to existing fused global estimates. Estimates at the global level that do not match those at the local level are birds that haven't been seen at that station yet and are removed from the association procedure before associating birds that are common to both levels. Fusing estimates belonging to different birds can lead to significant divergence of the global estimate from the local estimates and the true state, leading to erroneous results. The data association at this stage should therefore be made with a high degree of certainty. In order to ensure correct data association, the Joint Compatibility Test is used [31]. The Joint Compatibility Test computes the Mahalanobis distances for all possible associations. The configuration that leads to the minimum total distance between states is picked as the best data association. Since this is a computationally expensive procedure, especially with a higher number of birds, local and global states that match strongly are associated before carrying out the Joint Compatibility Test, and only weak associations between states are resolved using this procedure.

It is also possible that significant information to assist in data association will be available from the image itself (e.g. from an intensity histogram of the pixels identified as belonging to a bird). However, that has not been considered here.

3.3 Estimation

A set of stations, each consisting of a camera pair, a processor and a two-way communication link form the components of the distributed system to be employed for estimating the position and velocity of the birds in view. As described in Section 2.3.1, the parameters to be estimated are given by the following state vector:

$$\mathbf{x}_{b,i}^o = \begin{bmatrix} x_{b,i}^o & y_{b,i}^o & z_{b,i}^o & \dot{x}_{b,i}^o & \dot{y}_{b,i}^o & \dot{z}_{b,i}^o \end{bmatrix}^T \tag{3.14}$$

It is necessary to spread the cameras out along the ridge at multiple viewing angles in order to lower Dilution of Precision. A Sigma Point Kalman Filter may be used to easily fuse the available measurements at a central processor to compute one estimate. However, this approach makes the operation of one processor critical to the performance of the entire system. Also, a failure in communication system leads to the complete loss of track. Alternatively, a hierarchical approach is proposed for this project, wherein bearings from pairs of cameras are fused using an Unscented Kalman Filter (UKF)[32, 16] to compute independent estimates at numerous stations.

3.3.1   Computing Local Estimates

Each set of stereo cameras is equipped with a processor, transmitter and receiver. The bearing measurements are obtained using Equations 2.12 and 2.10. Track to a bird is initialized using the Particle Filter when it first enters the FOV of any of the cameras, as presented in Section 3.1. Once an initial estimate, $\hat{\mathbf{x}}_0$, and its covariance, $\mathbf{P}_0$, are obtained, the tracking is carried out by the Unscented Kalman Filter (UKF).Since the state estimates for different birds are uncorrelated a separate UKF is initiated for each bird as it enters the field of view. The prediction step is driven by the bird kinematics described in Section 2.3.1. The flight dynamics are continuous but the measurements are available at a discrete rate of 30 Hz, for a camera that grabs 30 frames per second. The equations are therefore modified from continuous time to discrete time. $\mathbf{A}_d$ and $\mathbf{B}_d$ are the discretized versions of the continuous system state space model, $\mathbf{A}$ and $\mathbf{B}$, which are defined in the flight dynamics model given by Equations 2.1 through 2.4. $\mathbf{A}_d$ and $\mathbf{B}_d$ can be computed as follows:

$$\mathbf{A}_d = e^{\mathbf{A}\Delta t} \tag{3.15}$$

$$\mathbf{B}_d = \mathbf{A}_d \left[\mathbf{I} - e^{-\mathbf{A}\Delta t} \right] \mathbf{A}^{-1} \mathbf{B} \tag{3.16}$$

Since the motion of the bird is linear, the prediction step can be simplified to those given by the Kalman Filter. The a priori state, $\mathbf{x}_{k|k-1}$, and the associated covariance, $\mathbf{P}_{k|k-1}$, of bird b at the current, k^{th} time step, given its position at the

previous, k-1th time step, are predicted by the following equations:

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{A}_d\hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_d u_{k-1} \tag{3.17}$$

and

$$\mathbf{P}_{k|k-1} = \mathbf{A}_d\mathbf{P}_{k-1|k-1}\mathbf{A}_d^T + \mathbf{Q} \tag{3.18}$$

where u is the input to the system, which in this case is zero since there is no external input and $\mathbf{Q}$ represents the additional process noise in the system which accounts for uncertainty due to unmodeled system dynamics like bird acceleration.

The measurement model is non-linear due to the trigonometric functions used to compute the bearings to the bird. The Unscented Kalman Filter (UKF) introduced in Section 2.4.2 overcomes non-linearities by propagating a set of particles with a pre-determined distribution through the system and estimating the state of the system and the associated covariance by computing the statistics of these particles. The correction step of the UKF is implemented for the measurement update step in the bird tracking problem so that a reliable estimate may be computed despite the non-linear equations in the measurement model. The correction for the predicted state, $\hat{\mathbf{x}}_{k|k-1}$, and covariance, $\mathbf{P}_{k|k-1}$ to compute the a posteriori estimates , $\hat{\mathbf{x}}_{k|k}$ and $\mathbf{P}_{k|k}$, is computed using the following equations of the UKF measurement update [16]:

$$\mathbf{X}_{k|k-1} = \begin{bmatrix} \hat{\mathbf{x}}_{k|k-1} & \hat{\mathbf{x}}_{k|k-1} + \eta\sqrt{\mathbf{P}_{k|k-1}} & \hat{\mathbf{x}}_{k|k-1} - \eta\sqrt{\mathbf{P}_{k|k-1}} \end{bmatrix} \tag{3.19}$$

where $\mathbf{X}_{k|k-1}$ is set of 2n+1 states that encompass the predicted state $\hat{\mathbf{x}}_{k|k-1}$ symmetrically along each of the dimensions of its state at a distances determined by the square root of the predicted covariance $\mathbf{P}_{k|k-1}$ and a scale factor η. The square root is computed using Cholesky decomposition which factors the matrix to a positive semi-definite matrix and its transpose. Once the sigma-points, $\mathbf{X}_{k|k-1}$, are computed, the bearings to each of these 2n+1 points is computed by propagating them through the measurement model defined in Section 2.3.2. $\mathbf{Z}_{k|k-1}$ is the matrix containing the bearings computed for each of the sigma points that lie within the

field of in view of the cameras. The weighting vector, $\mathbf{w}_m$, and weighting matrix, $\mathbf{W}_c$, are weighting parameters used to compute the mean and the covariance of the sigma points respectively and they are tabulated in Appendix A. The mean measurement of the sigma points is:

$$\hat{\mathbf{z}}_{k|k-1} = \mathbf{Z}_{k|k-1}\mathbf{w}_m \tag{3.20}$$

The measurement variance is computed by the following equation:

$$\mathbf{P}_{zz} = \Big[\ \mathbf{Z}_{k|k-1} - \hat{\mathbf{z}}_{k|k-1}\mathbf{1}\ \Big]^T \mathbf{W}_c \Big[\ \mathbf{Z}_{k|k-1} - \hat{\mathbf{z}}_{k|k-1}\mathbf{1}\ \Big] + \mathbf{R} \tag{3.21}$$

where $\mathbf{R}$ is the variance due to measurement noise in the cameras.

The covariance between the measurements and the prediction of the state is:

$$\mathbf{P}_{xz} = \Big[\ \mathbf{X}_{k|k-1} - \hat{\mathbf{x}}_{k|k-1}\mathbf{1}\ \Big]^T \mathbf{W}_c \Big[\ \mathbf{Z}_{k|k-1} - \hat{\mathbf{z}}_{k|k-1}\mathbf{1}\ \Big] \tag{3.22}$$

The Kalman gain is therefore:

$$\mathbf{K} = \mathbf{P}_{xz}\mathbf{P}_{zz}^{-1} \tag{3.23}$$

The correction step is carried out to compute the a posteriori state estimate, $\hat{\mathbf{x}}_{k|k}$, and covariance, $\mathbf{P}_{k|k}$, given the measurements from the cameras at the current time step, $\mathbf{z}_k$, is as follows:

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}\Big(\ \mathbf{z}_k - \hat{\mathbf{z}}_{k|k-1}\ \Big) \tag{3.24}$$

and

$$\mathbf{P}_{k|k} = \mathbf{P}_{k|k-1} - \mathbf{K}\mathbf{P}_{zz}\mathbf{K}^T \tag{3.25}$$

The tracking procedure described above is carried out at every node to get local estimates $^L\hat{\mathbf{x}}_{k|k}$ and covariance $^L\mathbf{P}_{k|k}$. In order to compute the best possible estimate of the bird state, all available local estimates are combined to compute a global estimate $^F\hat{\mathbf{x}}_{k|k}$ and covariance $^F\mathbf{P}_{k|k}$.

3.3.2 Computing Global Estimates

The local estimates computed as documented in the previous section, are transmitted to a central processor via the communication link. The central processor fuses all available estimates and transmits a global estimate back to all stations, which is used by each station to correct its prediction for the consequent time step. Although this approach still relies on the central processor for fusing the estimates, its operation is not critical. The load on the processor has been reduced significantly, and in the event of its failure, track is still maintained at each station. It is important to realize that the estimates from each station are not entirely independent and that they share the same process noise. Assuming independence while fusing local estimates will lead to an overconfidence in the estimated state caused by adding the same information repeatedly. A number of algorithms have been developed to fuse estimates from various stations, specific to the flow of information in the distributed system [20]. A global state fusion algorithm based on the information form of the Kalman Filter is employed, which accounts for the correlation of local estimates [33]. An unbiased estimate is achieved by subtracting the predicted estimate and covariance of each station from their corrected values, to account for the correlation between node estimates, before adding them to the global predictions of covariance and estimates. The global, a posteriori estimate, $^{F}\hat{\mathbf{x}}_{k|k}$, and the associated covariance $^{F}\mathbf{P}_{k|k}$ can be obtained from the following equations[20]:

$$^{F}\mathbf{P}_{k|k}^{-1} = {}^{F}\mathbf{P}_{k|k-1}^{-1} + \sum_{i=1}^{n}({}^{L}\mathbf{P}_{i,k|k}^{-1} - {}^{L}\mathbf{P}_{i,k|k-1}^{-1}) \tag{3.26}$$

$$^{F}\mathbf{P}_{k|k}^{-1}{}^{F}\hat{\mathbf{x}}_{k|k} = {}^{F}\mathbf{P}_{k|k-1}^{-1}{}^{F}\hat{\mathbf{x}}_{k|k-1} + \sum_{i=1}^{n}({}^{L}\mathbf{P}_{i,k|k}^{-1}{}^{L}\hat{\mathbf{x}}_{i,k|k} - {}^{L}\mathbf{P}_{i,k|k-1}^{-1}{}^{L}\hat{\mathbf{x}}_{i,k|k-1}) \tag{3.27}$$

The fused covariance and estimates thus obtained are transmitted back to all the stations an a time update is carried out by each station on the fused estimate from the previous time step to obtain a priori estimates:

$$^{L}\mathbf{P}_{i,k|k-1} = {}^{F}\mathbf{P}_{k|k-1} \tag{3.28}$$
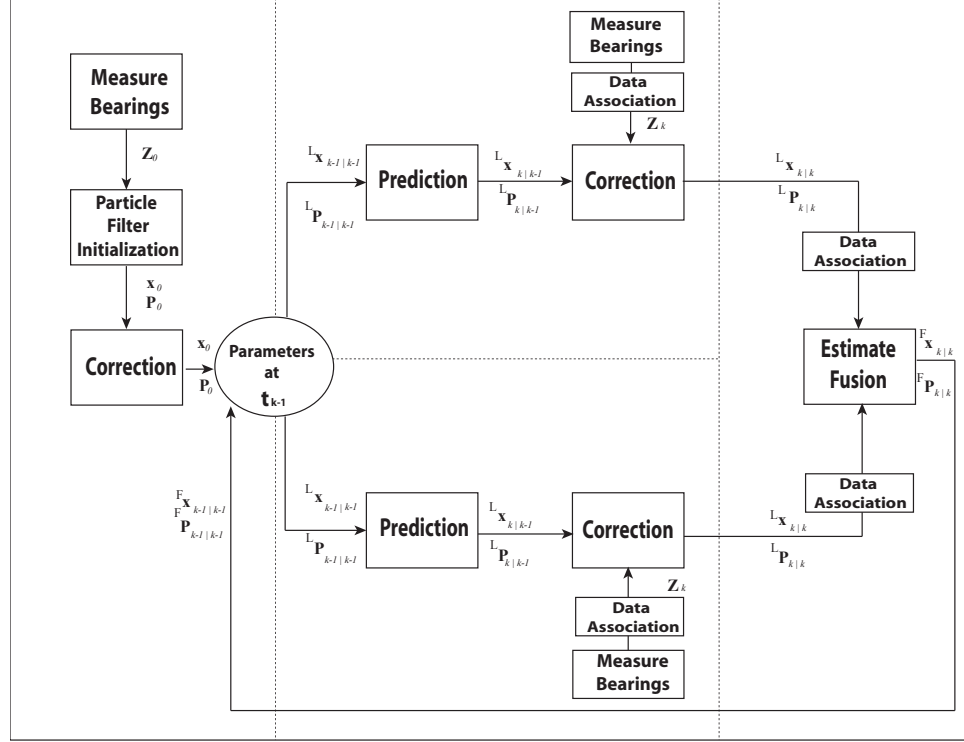
Figure 3.2. Data Flow

$$^{L}\hat{\mathbf{x}}_{i,k|k-1} = {}^{F}\hat{\mathbf{x}}_{k|k-1} \tag{3.29}$$

Transmitting the fused estimates back to all stations ensures that there is no drift between stations over time and all stations benefit from the information from all other stations at each time step, which leads to an improved estimate in the next time step.

3.4   Data Flow

The data flow through the estimation process for every bird in the flock, from the time it enters the field of view to the time it leaves it, is shown schematically in Figure 3.2

At flight starting time t_0:

- The initial position of the bird in view is estimated using a Particle Filter. A velocity is chosen based on documented bird speeds and augmented to the

estimated position to obtain the initial state $\hat{\mathbf{x}}_0$ and $\mathbf{P}_0$.

At an intermediate time t_k:

- Global estimates
  $^F\hat{\mathbf{x}}_{k-1|k-1}$ and $^F\mathbf{P}_{k-1|k-1}$ or $\hat{\mathbf{x}}_0$ and $\mathbf{P}_0$ from the previous time step are available.

  At every node i:

  - Prediction
    The global estimates $^F\hat{\mathbf{x}}_{k-1|k-1}$ and $^F\mathbf{P}_{k-1|k-1}$ are put through the time update step given by Equations 3.17 and 3.18 to obtain local a priori estimates $^L\hat{\mathbf{x}}_{k|k-1}$ and $^L\mathbf{P}_{k|k-1}$.

  - Measurement
    Procure measurements from each camera that views the bird using the measurement model described in Section 2.3.2. Add measurement noise to simulate real sensor measurements.

  - Data Association of Measurement
    Data association is computed from camera to camera and frame to frame as described in Section 3.2.

  - Correction
    The measurements obtained are used to correct the Prediction by comparing the actual measurement to those estimated for the sigma points defined by Equation 3.19. The UKF measurement update defined in Section 3.3.1 is carried out to obtain a posteriori local estimates at each station, of the bird state, $^L\hat{\mathbf{x}}_{k|k}$, and covariance $^L\mathbf{P}_{k|k}$. These local parameters are all transmitted to the central processor

- Data Association of Local Estimates
  Data association of is carried out to reorder local estimates to match existing global estimates, as described in Section 3.2, before fusing to update the global estimates.

- Fusing Estimates

  The estimates computed at all the local nodes are fused at the central processor using Equation 3.26 and Equation 3.27, to obtain the global parameters. $^{F}\hat{\mathbf{x}}_{k|k}$ and $^{F}\mathbf{P}_{k|k}$. $^{F}\hat{\mathbf{x}}_{k|k}$ is the best estimate of the birds position and velocity at t_{k} and $^{F}\mathbf{P}_{k|k}$ is the covariance of the estimate.

Chapter 4

Bird Tracking Simulation Results

THE FOLLOWING CHAPTER PRESENTS the results obtained for a simulation designed to test the performance limits of the bird tracking system proposed in Chapter 3. The Monte-Carlo simulation consists of numerous flight paths at distances varying from 10 to 100 times the distance between stereo pairs. The simulation is programmed to represent the environment under observation and the sensors used to observe it. The primary purpose of the simulation is to test the performance of the tracking system proposed in the previous chapter to determine if it would satisfy the requirements of a viable bird tracking system at the proposed site. The simulation results presented address the following performance factors:

- The effectiveness of the track initiation process in formulating an initial estimate that is Gaussian enough to prevent estimator divergence and facilitate tracking within the desired limits of error.

- The effect of additional information at every time step on the Dilution of Precision, as the bird flies it course across the Field of View of the camera system.

- The comparison of explicitly computed to assumed Data association

- The level of accuracy of the tracking system and the consistency between true and estimated error.

- Comparison of the performance of a Distributed tracking system to that of a Centralized one.

- Analysis of the systems performance for various hardware and installation specifications.

The description of the simulated sensor system and the mathematical model of the bird dynamics and the simulation of their flight paths is described in Section 4.1. Monte-Carlo results for the factors listed above are presented in Section 4.2 along with the inference that may be formed from the trends observed.

4.1 Simulation Setup

The tracking of migratory raptors involves the estimation of the actual positions and velocity of birds viewed by a system of cameras in a user defined configuration. The true parameters of the birds being tracked are simulated and the estimated parameters are compared to these values in order to evaluate the performance of the tracking system. The distribution of the sensors and their performance parameters are also simulated to reflect actual geometric constraints of the tracking site and documented features of most off the shelf cameras.

4.1.1 Sensor System

The camera system is set up so as to best cover the area under observation with a low Dilution of Precision, DOP, while obeying the constraints set by the physical requirements of wiring the sensors to the processor and the terrain of the observation site. The distance between stereo pairs is dictated by the length of wiring available to connect the local set of stereo cameras to the processor at that station. The distribution of stereo systems is determined by the geographic properties of the ridge where the migration is being observed.

The results presented in this chapter are all products of a distributed sensor system consisting of 2 independent stations consisting of a two cameras each. At each local station, the two cameras are placed, one on the East axis of the global coordinate system, the other, 10 meters along the East and 10 meters along the North, making the effective distance between cameras about 14 meters. Local pairs point inwards at each other with a pan of 45 degrees. This causes the fields of view of both cameras to overlap considerably and lowers DOP. The groups of

stereo cameras can be separated by longer distances since each group has its own processor, and communication between stations can be carried out via a wireless system. Two groups of stereo pairs, 800 meters apart, are utilized in this project. Additional stations may easily be added and all of the above parameters can be changed by the user.

## 4.1.2   Flight Path and Bird Dynamics

The simulation is initiated with the bird at any point along the edge of the Field of View (FOV) of the first camera in the array of stations. The distance of the bird from the camera array is set up to be between 10 to 100 times the baseline of the stereo pairs, d, in the system. The time of flight for each bird, given the true velocity components, is computed as the amount of time it takes to pass through the Fields of View of all cameras and reach the opposite edge. The velocity of the bird is randomly chosen within a range of speed provided by Kerlinger [8]. The velocity in the East-West direction is high compared to that in the North-South or Up-Down direction since the birds in the simulation fly across the Fields of View of the cameras in the East-West direction.The number of birds in the simulation is specified by the user and the flight path of each bird is determined as described above. Simulating flight paths in this manner facilitates a thorough analysis of the problem at hand and tests the performance limits of the tracking system.

Table 4.1. Simulation Parameters	
Number of Runs	100
Number of Stations	2
Distance between Stations	800 meters
Cameras per station	2
Distance between Cameras	14.14 meters
Distance of Birds from Stations	150 to 1500 meters

4.2 Monte-Carlo Results

The routine of a set of birds flying across the Fields of View of the camera array, is carried out a large number of times, for different sets of bird parameters. The true and estimated positions and the covariance are recorded at every time interval for all runs. The Monte-Carlo results for 100 runs are presented in the following section for the three aspects of the tracking routine presented in Chapter 3. The simulation parameters used for computing all the results presented in the following section are listed in Table 4.1 and the setup is depicted in Figure 4.1.
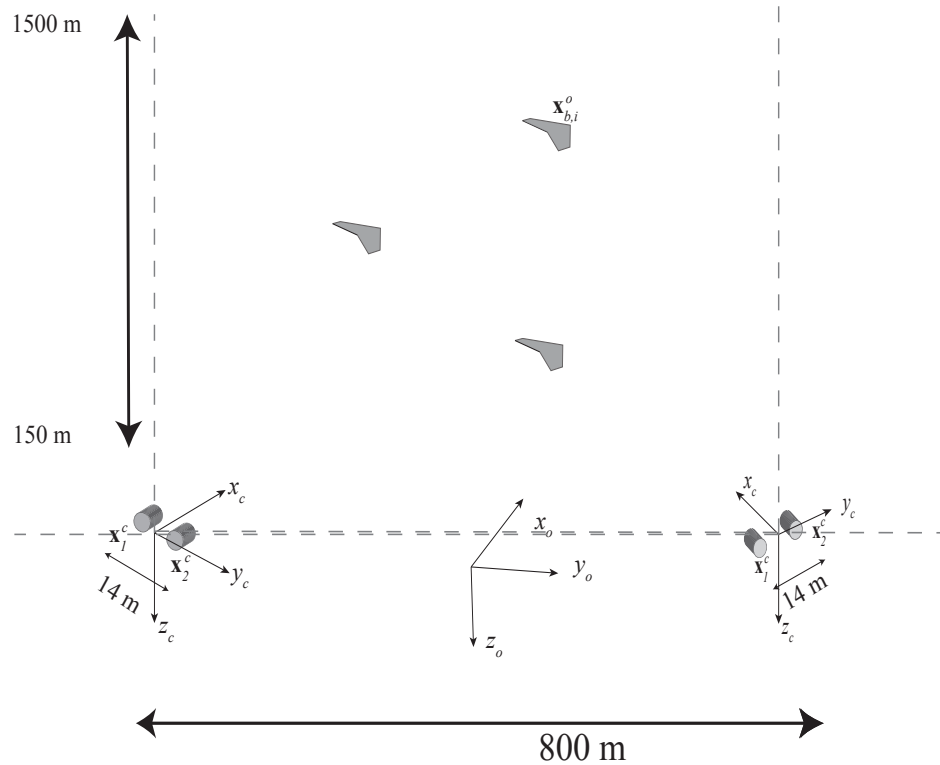
Figure 4.1. Simulated setup for the bird tracking system.
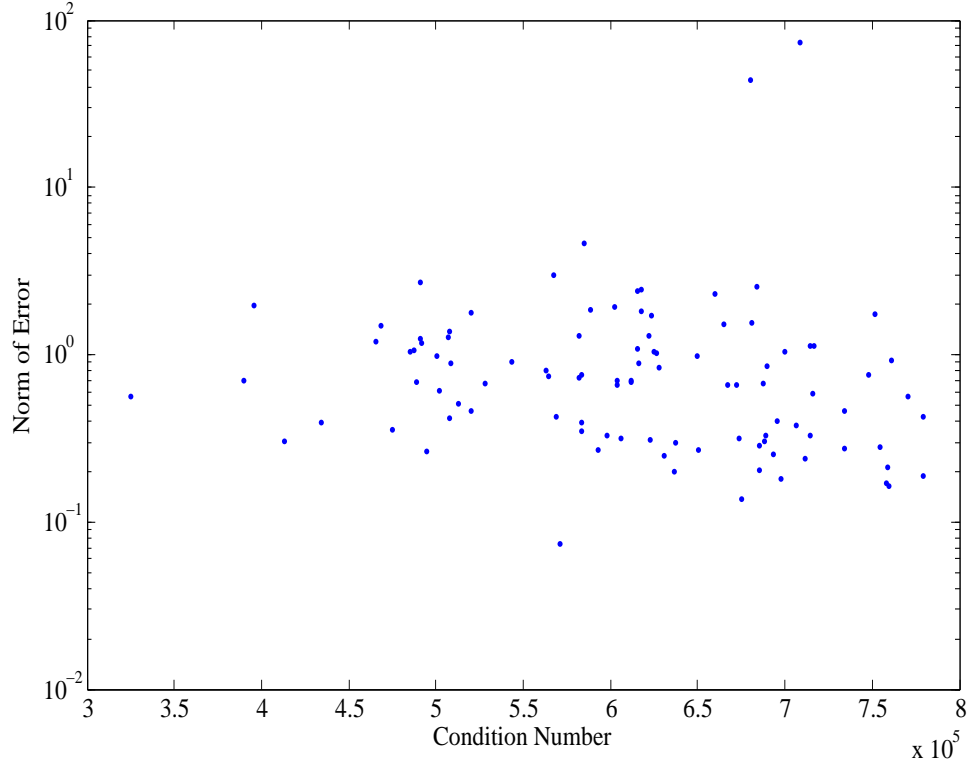
4.2.1 Track Initiation

Figure 4.2. Monte Carlo simulation results of initialization parameters.

The track is initiated using a particle filter as described in Section 3.1 is carried out when the bird is first viewed by any of the cameras in the distributed systems. Cameras that consequently view the bird initiate the track using the current global estimate of the bird. The initialization of the bird involves making use of the first set of information to formulate a viable initial estimate of the bird. It is a heuristic process that depends on the strategic formulation of an initial set of particles, using a weighting procedure to compute an initial estimate and its covariance. Since the uncertainty along the bearing is higher than that across, due to DOP , the uncertainty ellipse obtained from the initialization step is skinny and has a high condition number. Intuitively, a high condition number can cause an ambiguity that can cause the estimator to diverge exponentially. Figure 4.2 shows a scatter plot of the true position error at the time of initialization vs. the condition number of the covariance associated with the initial estimate, obtained from the initialization step in the 100 run Monte-Carlo Simulation. Note that

condition number, on the order of 10^5, is very high, which can be attributed to the distance of the bird from the station at the time of initialization and the lack of more measurements. The error in the estimate, however, does not exceed 100 meters for the even the highest of condition numbers at the time of initialization. Although the initialization is highly uncertain, the estimator recovers from it in a few time steps and it does not affect the performance of the tracker much.

4.2.2 Tracking Performance

The path of a bird flying through the field of view for five different runs is shown in Figure 4.3. It can be seen that the estimated position of the bird closely matches the true position and the covariance ellipse reduces with time. Initially, the ellipse is strongly elongated along the bearing from the camera to the bird: this is caused by the relatively small baseline between the cameras which causes dilution of precision along the bearing.Although the covariance of the estimate at the time of initialization has a high condition number, especially at further distances from the camera, it remains within 3 standard deviations from the true bird position. It can also be noted that despite poor initialization, the UKF is able to converge to an accurate estimate within a few time steps, as more measurements are collected. A closer view of the bird at a later time is shown in Figure 4.3. The uncertainty ellipse seen here is well conditioned and about a meter wide.

To assess estimate consistency we compare the mean of the estimated error variance, $\sqrt{\text{trace}(\mathbf{P})}$, with the mean of the 2-norm of the estimate error, $\sqrt{(\mathbf{x} - \hat{\mathbf{x}})^T(\mathbf{x} - \hat{\mathbf{x}})}$. Results in Figure 4.4 show the performance of the proposed distributed system that fuses independent estimates from all stations to compute a global estimate and covariance of the bird's state at each time step.
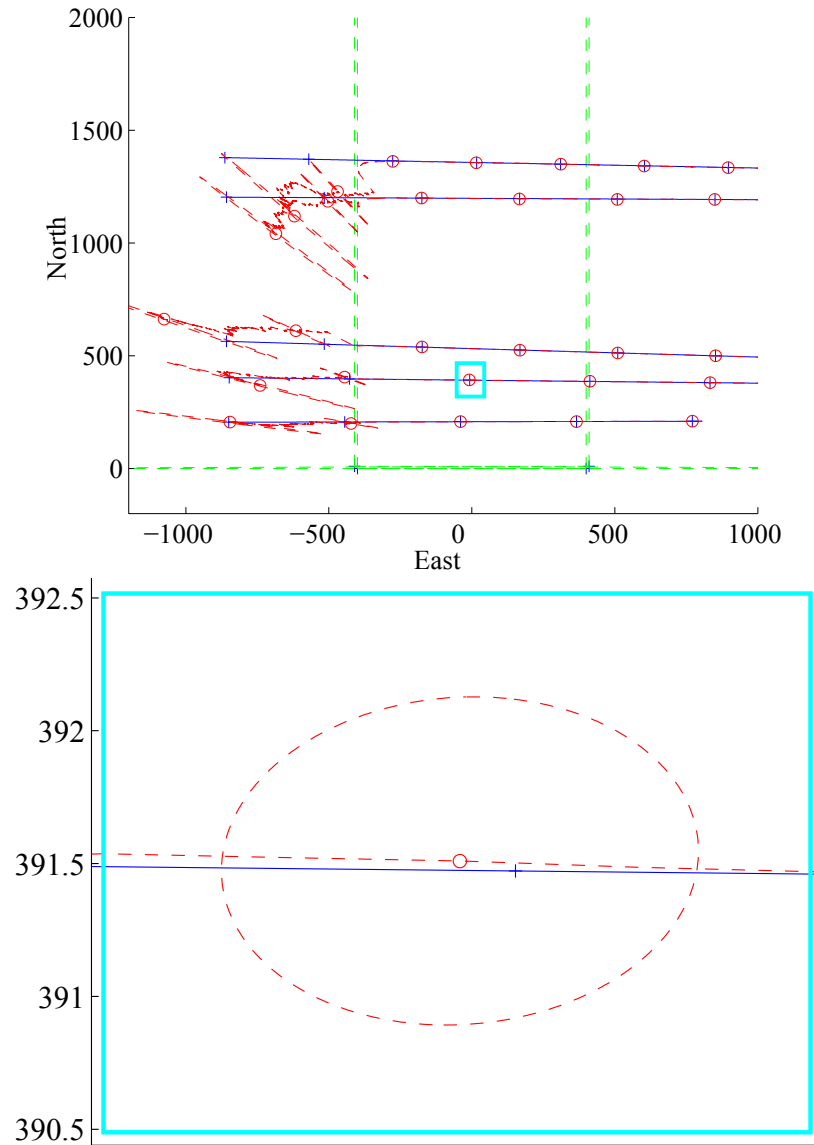
Figure 4.3. Tracking performance, projected onto the plane z=0. Green dashed lines depict field of view of the stereo cameras at two stations, facing each other at 45 degrees, the solid blue line and + show true bird positions, red dashed line and ellipsoids show 3-sigma position covariance and are centered on the estimated bird position. The lower plot shows the true and estimated positions of the bird and the associated uncertainty, at a later time in the flight path of the bird, after having obtained bearing measurements from both stations.

In order to cross check the performance of the distributed system, the same camera setup is used to simulate a centralized system with one processor and the result obtained is compared with those obtained for a distributed system. Since the information available to both systems is the same, the results should also be identical. Results in Figure 4.4 show the performance of a centralized system with one estimate and covariance computed from measurements from all stations.

The vertical axis shows true and estimated error on a logarithmic scale. The horizontal axis shows time normalized with respect to the total time a bird was within the field of view of both cameras. We can see that for most of the first half of time that the bird is in view, the estimator over-predicts the error in the position, indicating that the error predicted is more than the true error between the actual and predicted state of the bird. The estimate error dips sharply when the bird comes into view at both stations and the number of available measurements or estimates double. Once more information is obtained, the estimated and true error match each other consistently. Note that the results obtained by using a distributed system are identical to those obtained by the centralized system. Also, recall that the bird's velocity is assumed to vary by a random walk, and this uncertainty propagates into the position estimate. The average uncertainty in bird position once seen at two stations is 1 meter: note that the uncertainty in an individual bird's position will depend strongly on its distance from the cameras and the number of cameras where the bird is in view.
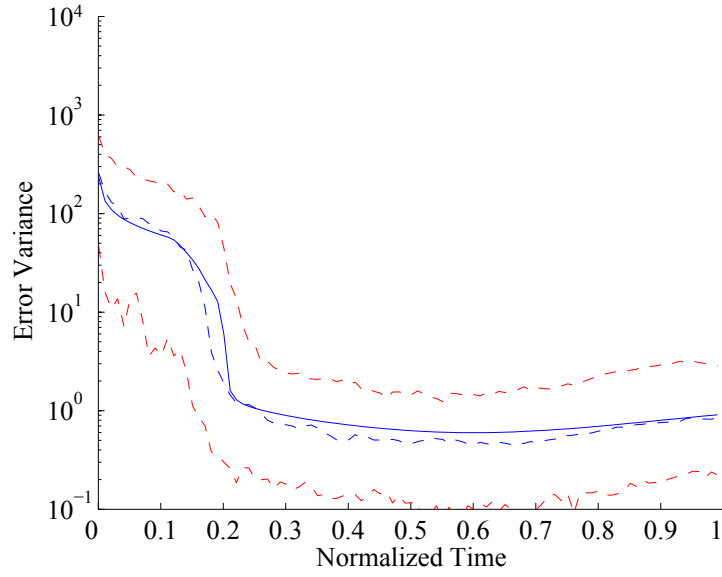
(a) Distributed System
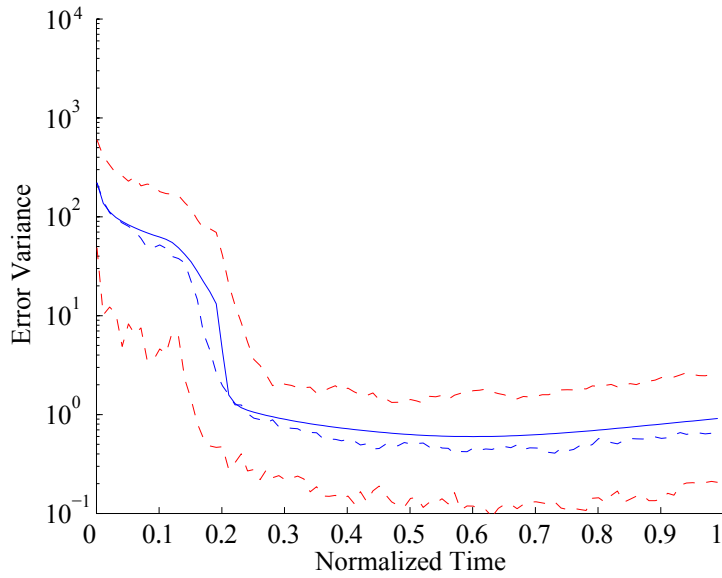
(b) Centralized System

Figure 4.4. Monte Carlo simulation results for a distributed and centralized systems. The dashed red lines show the maximum and minimum values of the 2-norm of the true estimate error, the dashed blue line shows the mean value of the 2-norm of the true estimate error and the solid blue line is the mean value of the estimated error variance.
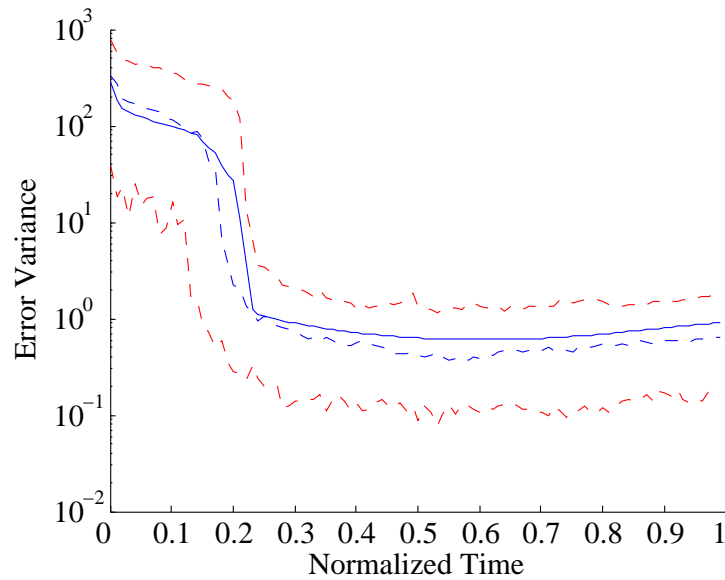
4.2.3 Data Association

The tracking procedures discussed assume that the measurements involved have a fixed order and the association between the measurements and the bird that it belongs to is known. The data obtained from the cameras, however, are bearing measurements to all the birds seen in each camera at a particular time period and the order is not know. Data association is computed to determine the relation between the measurements obtained from the camera and the state estimates being computed by the tracking system. Data association is carried out between stereo camera pairs and from frame to frame as described in Section 3.2. Moreover, data association is carried out before fusing local estimates as described in Section 3.2, to ensure that only local estimates that correspond to the same bird are fused to obtain a global estimate.

To assess estimate consistency we compare the mean of the estimated error variance, $\sqrt{\text{trace}(\mathbf{P})}$, with the mean of the 2-norm of the estimate error, $\sqrt{(\mathbf{x} - \hat{\mathbf{x}})^T(\mathbf{x} - \hat{\mathbf{x}})}$. Results in Figure 4.5 compare the performance of a system with explicitly computed data association to that of a system where the order of the measurements remains unchanged, and data association is inherent. It can be seen that the result in both cases match. Hence the data association procedures fulfil the tasks of maintaining the same order of measurements between cameras and over a sequence of frames, as well as rearranging local estimates to match the order of the global estimates they correspond to. Intermediate results for cases of partial data association and data association of more than three birds are presented in Appendix A.
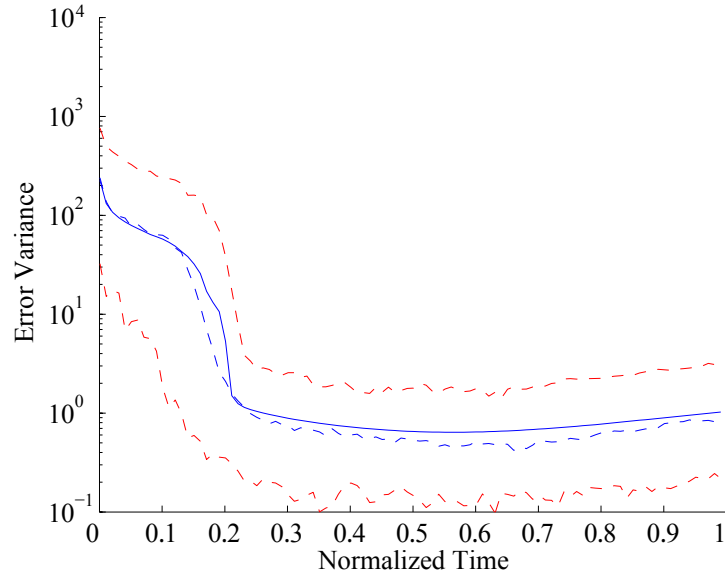
(a) System with inherent Data Association

(b) System with explicitly computed Data Association

Figure 4.5. Monte Carlo simulation results for systems with known and explicitly computed data association. The dashed red lines show the maximum and minimum values of the 2-norm of the true estimate error, the dashed blue line shows the mean value of the 2-norm of the true estimate error and the solid blue line is the mean value of the estimated error variance.

4.3 Hardware Selection Criteria

Selecting the right sensors is imperative in designing a system that not only provides data that is accurate enough to make a good contribution to migration research, but is not too sophisticated to be implemented using readily available hardware at any given site. Some of the implementation details that need to be considered are the distance between cameras at each local distance, or baseline, distance between stations in the distributed system, camera specifications, etc. Although the system presented in this thesis has been designed keeping realistic bearing noise and acceptable baselines in mind, a mathematical analysis of performance parameters for varying sensor configurations would provide a more in depth understanding of the effects of sensor specifications and locations on the accuracy of the estimate.

The number of pixels that represent a bird determine how much discernable information can be obtained from the scene. The cameras used should be able to detect birds that are several hundreds of meters away from the camera. The number of pixels that the bird takes up on an image depends on the distance of the bird from the camera, the focal length of the lens and the size of a pixel as shown in Equations 4.1 through 4.3.

$$N_{pixels} = N_x \times N_y \tag{4.1}$$

where

$$N_x = \frac{2 \times f \times w_{bird}}{d \times w_{pixel}} \tag{4.2}$$

and

$$N_y = \frac{2 \times f \times h_{bird}}{d \times h_{pixel}} \tag{4.3}$$

w_{bird} and h_{bird} are the wingspan and cross-sectional height of the bird and d is the distance of the bird from the camera. f is the focal length of the lens, and w_{pixel} and h_{pixel} are the width and height of a pixel respectively. The number of pixels occupied by the image of a bird with a wingspan of 2 meters and cross sectional height of 0.2 meters in relation to its distance from the camera is shown

Table 4.2. Camera Features

Camera Resolution	Focal Length	Pixel size	FOV	Noise
648×488	3.6mm	5.6×7.4 μm	$67° \times 53°$	$0.2°$
1032×776	2.9mm	4.65×4.65 μm	$79° \times 63°$	$0.1°$
1296×964	2.1mm	4.65×3.75 μm	$98° \times 81°$	$0.1°$

in Figure 4.6, for standard camera parameters.

The selection of the camera and corresponding lens defines the scope of the system. As seen in Figure 4.6, the resolution of the camera is an important factor in deciding how many pixels of data can be obtained from the image. The focal length of the lens for any given resolution plays a decisive role in the performance of the tracking system. While using a standard lens, with a relatively higher focal length, allows us to detect a bird at longer distances from the camera, it also reduces the FOV. Having a wide angle lens, with a short focal length, allows us to keep the bird in the image for a longer period of time, by consequently does not detect objects at further distances from the camera. Some trade-offs, therefore, have to be made to obtain the desired performance. Some camera parameters based on the specifications of commonly available cameras and wide angle lenses and are given in Table 4.2. The Field of View along the width or height of the scene is computed using Equation 4.4, where a is the width or height of the sensor on which the image is projected. The noise in bearing measurements can also be computed based on the FOV and pixel resolution. The error in bearing measurements may be approximated by Equation 4.5, where N_p is the number of pixels across the sensor and σ_{pixel} is the error due to pixel noise in the sensor.

$$FOV = 2 \times \text{atan}(\frac{a}{2f}) \tag{4.4}$$

$$\sigma_{bearing} \approx \frac{FOV}{N_p} \times \sigma_{pixel} \tag{4.5}$$

The difference in bearing measurements from different cameras in a stereo system is related to the difference in the position of the cameras, or baseline. Cameras that are far apart provide a more varied set of measurements as compared to those close together. This disparity in measurements provides more unique sets of information, leading to a better estimate of the position. The terrain at the site
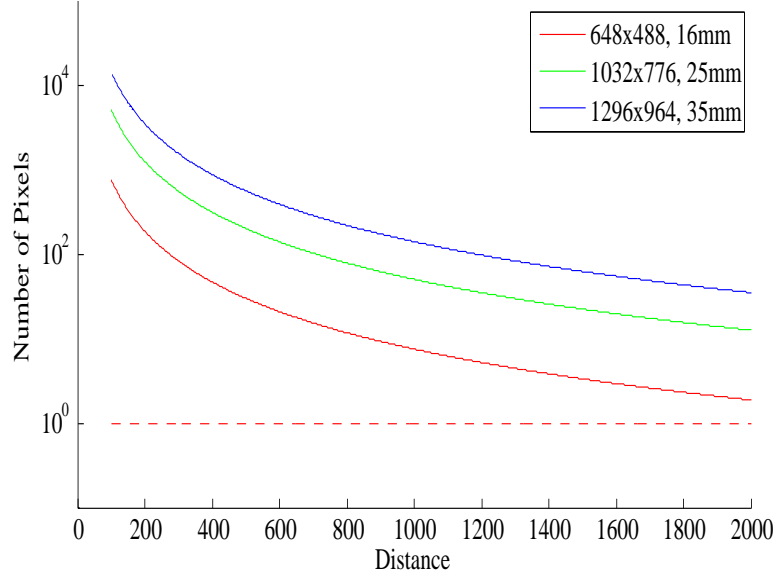
Figure 4.6. Number of pixels occupied by a bird on the image with respect to the distance in meters from the camera, for various camera specifications. The minimum number pixels required to detect a bird is assumed to be 1 and is marked by the dashed red line.

and wiring constraints, however, restrict the baseline of a stereo system. In order to determine the effect of the baseline on the error in the position estimate, an analysis of the measurement model is carried out. In the case of a system with m cameras that each provide an azimuth to the bird in view, the expected error in the 2D position estimate may be computed by the analysis presented.

The 2D position of a bird at location (x_b, y_b) in world coordinates can be expressed in the coordinates of a camera m as,

$$
\begin{bmatrix} x_{b,m}^c \\ y_{b,m}^c \end{bmatrix} = \mathbf{T}_m \begin{bmatrix} x_b - x_o \\ y_b - y_o \end{bmatrix} + \begin{bmatrix} \Delta x_m^c \\ \Delta y_m^c \end{bmatrix} \tag{4.6}
$$

where $\mathbf{T}_m$ is the rotation of the camera axis with respect to the world, (x_0, y_0) is the origin of the stereo camera system and $(\Delta x_m^c, \Delta y_m^c)$ is the displacement of camera m from the origin of the stereo system, in camera coordinates.

The azimuth to a bird from camera m is,

$$
\theta_m = \arctan\left(\frac{y_{b,m}^c}{x_{b,m}^c}\right) \tag{4.7}
$$

The measurement model described in this section is of the form,

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{v} \tag{4.8}$$

$\mathbf{y}$ being the measurements, $\mathbf{x}$ the state measured, $\mathbf{H}$ the measurement model and $\mathbf{v}$ being measurement noise of variance $\mathbf{R}$. For a linear system, the minimum variance estimate is computed by a weighted least squares procedure. The estimate is a Gaussian with mean $\hat{\mathbf{x}}$ and covariance $\mathbf{P}$, where,

$$\hat{\mathbf{x}} = (\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \mathbf{H}^T \mathbf{R}^{-1} \mathbf{y} \tag{4.9}$$

and

$$\mathbf{P} = (\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H})^{-1} \tag{4.10}$$

However, the measurement model of this system is a non-linear one. Computing the Jacobian of the measurement model, a measurement model, $\mathbf{G}$, linearized about a bird position (x_b, y_b), is obtained for an m camera system as follows,

$$\mathbf{G} = \begin{bmatrix} \frac{d\theta_1}{dx} & \frac{d\theta_1}{dy} \\ \frac{d\theta_2}{dx} & \frac{d\theta_2}{dy} \\ \vdots & \\ \frac{d\theta_m}{dx} & \frac{d\theta_m}{dy} \end{bmatrix} \tag{4.11}$$

where θ_m is the computed azimuth to the bird from camera m.

On computing the differentials, Equation 4.11 can be expressed as,

$$\mathbf{G} = \begin{bmatrix} \frac{-\sin\theta_1}{r_1} & \frac{\cos\theta_1}{r_1} \\ \frac{-\sin\theta_2}{r_2} & \frac{\cos\theta_2}{r_2} \\ \vdots & \\ \frac{-\sin\theta_m}{r_m} & \frac{\cos\theta_m}{r_m} \end{bmatrix} \tag{4.12}$$

where,

$$r_m = \sqrt{(x_{b,m}^c - x_m^c)^2 + (y_{b,m}^c - y_m^c)^2} \tag{4.13}$$

(x_m^c, y_m^c) being the 2D position of camera m in camera coordinates.

The covariance of the position estimate can therefore be computed based on Equation 4.10, and is given by,

$$\mathbf{\Sigma}_{position} = \left(\mathbf{G}^T \mathbf{\Sigma}_{bearing}^{-1} \mathbf{G}\right)^{-1} \qquad (4.14)$$

where $\mathbf{\Sigma}_{bearing}$ is the covariance of noise in bearing measurements. $\mathbf{\Sigma}_{bearing}$, also known as the sensor noise, is dependant upon the characteristic noise of the cameras used and varies with camera parameters like Field of View and pixel resolution as per Equation 4.5.

The error in the position estimate is predicted as $\sqrt{\text{trace}(\mathbf{\Sigma}_{position})}$.

For a two camera simple stereo system, where the baseline is the displacement between the two cameras along the y axis, the error in the position estimate can be computed for varying bird positions (x_b, y_b). Figure 4.7 shows the effect of increasing distance from the cameras on the estimated error in 2D position based on the measurement model, for baselines between 1 and 16 meters. Note that this estimated error in 2D position is the lower bound of the expected error for one set of measurements. The bearing noise assumed is 0.5 degrees. It is observed that the estimated error in position increases with distance, and having a larger baseline lowers the rate at which it increases.

Figure 4.8 shows the effect of increasing distance from the cameras on the estimated error in 2D position based on the measurement model, for sensor noise varying from 0.25 degrees to 1.5 degrees error in the bearing measurement. The baseline assumed is 10 meters. It is observed that the estimated error in position increases with distance, and lowering measurement noise curbs the rate at which it increases. A combination of various lens and camera parameters can give the desired degree of sensor noise.

Figure 4.7. Estimated error in the position estimate is plotted against increasing distance in meters from the origin of the stereo camera system. The plot is repeated for varying baselines of 1 through 16 meters.
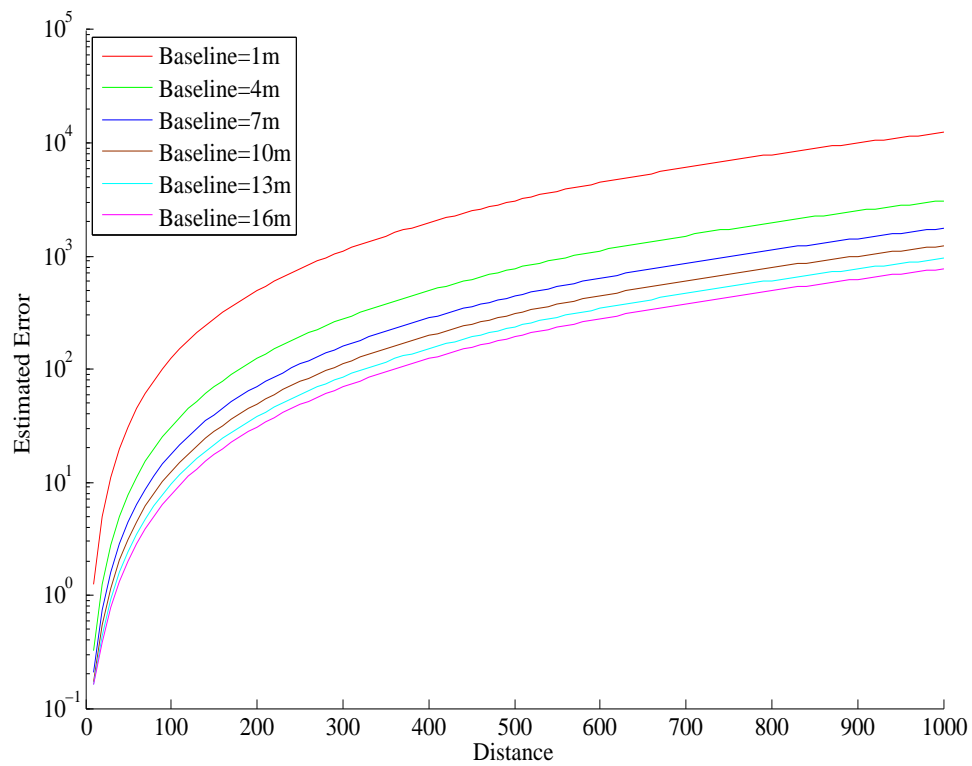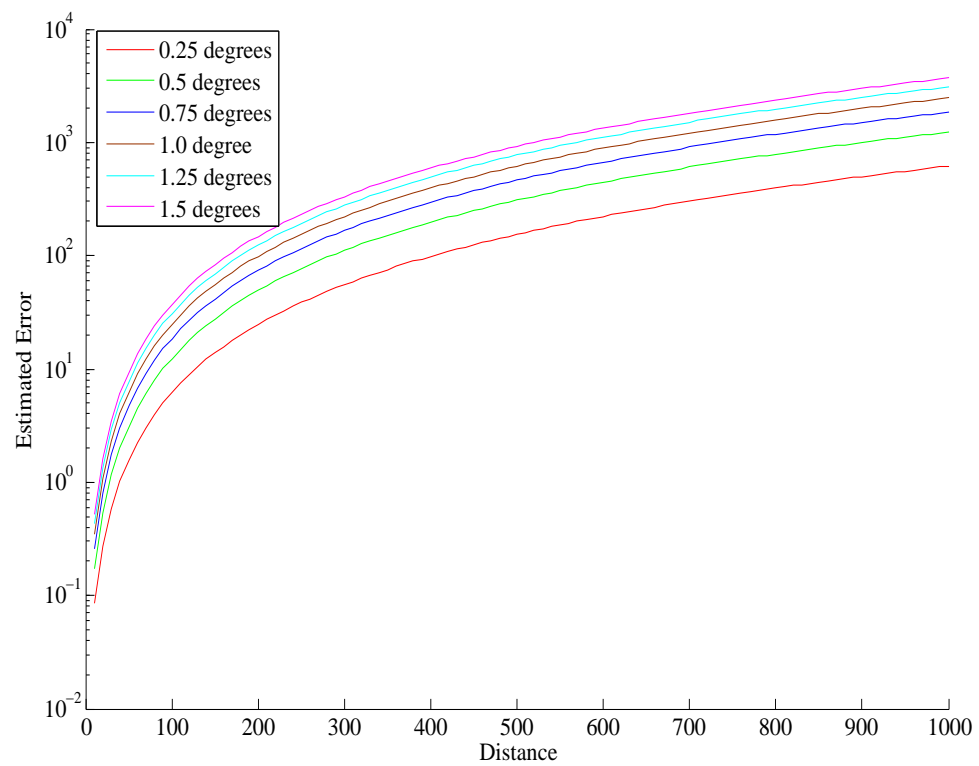
Figure 4.8. Estimated error in the position estimate is plotted against increasing distance in meters from the origin of the stereo camera system. The plot is repeated for sensor noise of 0.25 through 1.25 degrees of error in the bearing measurement.

4.4   Summary

The simulation of the bird tracking system as described in this chapter yielded the following results for the performance parameters listed below:

- **Track Initiation:** The error in the position estimate of the bird on initialization remains lower than 100 meters even for condition numbers in the order of 10^5 at track initiation. The estimates obtained from the initiation process never caused the estimator to diverge and led to state estimates that were accurate enough to tabulate the migratory route.

- **Dilution of Precision:** The error ellipse is elongated over the first few time steps due to the higher Dilution of Precision along the optical axis. The error ellipse shrinks over the consequent time steps and becomes more rounded, due to the information added with time.

- **Tracking Performance of a Distributed System:** The error in the estimated position is bounded within the required accuracy. The error decreases with time and drops sharply with the addition of more sensors. The true error coincides with the error predicted by the covariance of the computed estimate.

- **Tracking Performance of a Centralized System:** The tracking performance of the Centralized system is identical to the Distributed system and confirms that the estimate obtained from one processor matches the fused estimate computed from multiple processors.

- **Tracking Performance under explicit Data Association:** The performance of the the tracker without the knowledge of the number and sequence of birds at each station is tested. The correspondence between measurements from different sensors over time and the relation of local estimates to the fused global estimates is computed explicitly. The tracking performance with explicitly computed data association matches the tracking performance with known data association.

- **Hardware based Performance Evaluation:** An analysis of performance parameters, including the number of pixels and estimated error for one set

of measurements is computed for several configurations of sensor and installation specifications. It is found that the performance goals can be met with practically feasible hardware configurations.

The results presented in this chapter imply that the proposed system will perform favorably as an autonomous bird tracking technique. The problem of tracking small objects from a large distance, given a non-linear measurement model and a distributed network of sensors has been dealt with to obtain state estimates of migrating raptors with the desired level of accuracy. The implication of these results and future work for improved functionality of this system are discussed in Chapter 5.

Chapter 5

Conclusion

T RACKING MIGRATING RAPTORS along routes adjacent to possible wind farm
locations has been the motivation for the distributed tracking system proposed
in this thesis. The danger that windmills may pose to birds flying along these routes
is a threat that has yet to be quantified. The specific knowledge of these routes
is required to estimate the effect of wind farms on migrating species. Present bird
monitoring techniques rely heavily human input and are therefore time consuming,
expensive and non uniform. Having an autonomous system that continuously
monitors a given site for migratory behavior would be both effective and reliable.
An inexpensive set of sensors, like off-the-shelf cameras, will ensure that minimum
capital is required to provide essential information at a low cost. The system
described in this thesis has been designed with these factors in mind so that sources
of renewable energy may be developed without endangering species of birds that
share the same sky.

Tracking from long distances using low-resolution and noisy measurement is a
difficult problem prone to significant uncertainty and Dilution of Precision(DOP).
The measurement model, which involves computing bearings using trigonometry,
makes the estimation a non-linear one. The problem of non-linear estimation can
be tackled by using one or more of the textbook non-linear Kalman filters. DOP
may be lowered by using a spatially spread out and symmetric geometry of sensors
so that ambiguities in various directions may cancel each other out. The limita-
tions provided by the terrain of the geographic site and the physical constraints
of the hardware have motivated the construction of a Distributed System. The

Distributed System consists of independent tracking stations consisting of a stereo pair and a processor, each computing independent estimates. Local estimates are then fused to provide the resulting higher priority state estimate which is the current best estimate. The fusion algorithm must account for the shared process noise among all local stations in order to avoid overconfidence in the state estimate.

Track is initiated when a bird is seen at any of the local stations for the first time. Since no prior information is available to the tracking system regarding the state of the bird, the Particle Filter is used to compute an initial estimate and covariance of the bird, that are Gaussian enough to be used as initial estimates in the Sigma Point Kalman Filter (SP-KF). A Gaussian set of particles, or possible states, is generated in a solid angle about the fist bearing measurement obtained. The measurements from the other cameras that view the bird are then used to provide a weight for each particle based on how closely the proposed measurement for that particle matches the true measurement to the bird in view. The weighted mean and covariance of these particles provide the initial estimate and associated covariance for the state of the newly seen bird. This initial estimate is Gaussian enough to be used as an initial estimate in the SP-KF without causing it to diverge. Once track is initiated at a particular station, track is maintained by performing motion and measurement updates using the SP-KF to compute independent estimates at each time step. Should a previously seen bird come into view at another station, track is initiated with the best available estimate. Consequent estimates are obtained by fusing all the available local estimates of the bird.

The assumption of data association is inherent in the Kalman filter although the sensors do not perform data association, they only provide a set of measurements, the association of the measurement set to the birds being tracked has to be computed explicitly. The data association has to be performed between pairs of cameras to ensure that the pair of bearing measurements from the stereo pair at each station correspond to the same bird. Data association also has to be performed from frame to frame so that a correspondence is maintained between bearing measurements obtained from one frame to the next. The camera-to-camera correspondence of measurements is computed by checking the epipolar constraint between the stereo pair. If the epipolar constraint is satisfied, the measurement from both cameras belongs to the same bird. The measurements obtained from one

camera are therefore reordered to correspond with the measurements to birds seen by its stereo pair. Similarly, the gated Mahalanobis distance between the estimated state vector in the present and previous frame, is used to perform frame-to-frame data association. The combination with the minimum distance provides the correspondence between one frame to the next. Data association is also carried out before fusing local estimates to obtain one fused global estimate for each bird to determine which local estimates correspond to the same bird and fusing them appropriately. It is important to ensure that each bird corresponds to only one other bird in the next frame to avoid the double copy of one bird and the loss of another from the track.

The Monte-Carlo simulation of the described system was carried out for a variety of flight paths. It was found that despite the high DOP of the initial estimate, the error converges with information obtained in consequent time steps and the initial estimate is Gaussian enough to be used in the SP-KF without causing it to diverge. The SP-KF was found to perform favorably given the non-linearities in the system. The deterministic configuration of the Sigma Points propagated through the system equations, maintain a Gaussian distribution about the state estimate through the non-linear transformations, so that Kalman Filter based tracking may be carried out. The estimated error is found to correspond with the true error and remains bounded. Both the true and estimated error drop sharply with an increase in the number of measurement available. Results are shown for both distributed and centralized systems. Both results are identical since the information available to both systems is the same. The results of a system with explicitly computed data association are compared to the results for a system where the data association is inherently assumed. The results are found to match, which indicates that the association method gives results in the correct correspondence between camera-to-camera, frame-to-frame and between sets of local estimates.

5.1 Summary of Contributions

5.1.1 A novel bird observation technique

A cost effective method that can continuously monitor the flight path of birds around the observation site with minimal or no human input, can provide valuable information about the migratory patterns of the birds without incurring the capital of employing more people or buying specialized equipment. A continuous and autonomous method has been proposed that can keep track of the position and velocity of the birds in view. The system, consisting of a set of off-the-shelf cameras and processors, does not require a great deal of fiscal or labor input. Stereo-cameras can provide depth information based on epipolar constraints, and allow 3D estimation from 2D image information. The distribution of cameras can be specified based on the geography of the observation site. Bird dynamics and the measurement model are simulated based on expected behavior and physical constraints. The results of the proposed system on the simulation show that a fairly accurate track of individual birds is maintained even from large distances.

5.1.2 Application based estimator designs

The choice of states is a trade-off between the complexity of the estimation process and the information required to form a complete picture of the migratory route. The state vector chosen consists of the 3D position and velocity components. Bearings to the bird from each of the cameras in the system, are chosen for the measurements. Since the measurement model used to compute these bearings contains trigonometric functions, the estimation process becomes non-linear. The variations of the Kalman Filter for non-linear estimation were all considered and the Square Root form of the Unscented Kalman Filter was chosen. The Square-Root UKF was chosen due to its ability to generate consistent estimates without divergence and its computational efficiency. The prediction and correction equations were derived based on the bird dynamics and measurement model, respectively. The UKF requires an initial estimate and covariance, having a Gaussian distribution, in order to carry out the subsequent estimation procedure. The only information available when the bird first comes into view is a set of bearings from all the cameras that

view it. Several geometric triangulation approaches were tested before the Particle Filter was employed. A specific initialization process was designed to compute an initial estimate that led to satisfactory results once fed to the UKF . A set of particles, having a Gaussian distribution, are created in a solid angle about a bearing and weighted proportional to the similarity between the expected bearing measurements to it and the available bearings to the true position of the bird. The weighted mean and covariance are computed to obtain an initial estimate for the 3D position of the bird and its covariance. It is found that using arbitrary velocity components based on the expected velocity of the bird is sufficient for initialization purposes, since the deviation of velocity from its expected values is much lesser than that of position. Further, after obtaining the 3D position estimate using the Particle Filter and augmenting it with an arbitrary velocity vector, a measurement update is carried out on this initial state estimate in order to get a Gaussian estimate of the state and the covariance associated with it. This initialization process, that employed the Particle Filter, although heuristically designed, gave better initial estimates than plain trigonometry. The results obtained from this process, are stable and Gaussian in nature and allow the UKF to compute fairly accurate estimates, without causing divergence. The performance of the estimators designed is tested for multiple different tracking runs and satisfactory results are obtained.

5.1.3   Distributed implementation

Using more than one processor is not only computationally more efficient, but also robust to processor or communication failure. Moreover, should additional sets of measurements, like color information, become available, the distributed implementation is better suited to incorporate them since each processor computes an independent estimate. The interaction between various sensors and their relation to the final estimate can be designed depending on the nature of the system under observation. A Distributed Hierarchical system is designed such that each stereo camera pair in the system sends its measurements to a local processor that computes an independent local estimate. All local estimates are communicated to a central processor via wireless communication and fused to compute a higher priority global estimate. The fusion computation accounts for the shared process

noise by subtracting the information that has been added multiple times from the covariance to ensure that the accuracy of the estimate remains bounded by the noise present in the system. Once a fused estimate is computed, it is regarded as the current best estimate and is transmitted back to all the local processors. This step is important since it puts all the local estimators on the same level of certainty at each time step and averts the possibility of a drift of local estimates from each other. The system designed as described is tested against the conventional centralized implementation and results are found to be identical, as expected, since the information available to both systems is the same. The distributed implementation of the system, however, has the added advantages of being easier to implement physically, more computationally efficient, robust and versatile to a variety of measurements.

5.1.4 Performance Verification: Simulation

A Monte-Carlo simulation consisting of a number of varying flight paths is run to test various aspects of the estimation process. The properties of the initial estimate are compared to the error that the final estimate for each run converges to. It is found that even for initial covariances with a high Dilution of Precision, the error in the final estimate remains reasonable and bounded. The mean squared error in the estimate for all estimates, is compared to the square root of the trace of the covariance of the estimate as computed by the UKF and they are found to correspond with each other. Hence proving that the estimated error is found to match the true error. The performance of the distributed implementation is compared to that of the centralized version and both results obtained are identical as expected. This indicates that the fusion technique employed is representative of the interaction between estimators and accounts for the process noise shared among them. The advantage of a distributed system over a centralized one can therefore be exploited at no loss to the quality of the tracking system's performance. The performance of a system with known data association is compared to the implementation where data association is computed explicitly, and both results match closely. The data association procedure, especially for a small number of birds, provides satisfactory results.

5.2   Recommendations for Future Work

5.2.1   Simulation Details

The simulation designed so far has a fixed number of birds in view, initialized at the first time step and does not address the problem of continuous track initiation and deletion. For a more realistic depiction of a continuously running system, birds have to be designed to come into view at varying time steps. In such a case, the track initiation routine will have to be invoked whenever a new bearing is available at a station. Data association needs to be carried out between the new bearing and the estimates bearings to all global bird estimates from this station in order to ensure that there are no duplicate estimates. Also, birds that have gone out of view at all stations have to be removed from the list of fused estimates. A more detailed simulation that accounts for communication dropouts and birds being temporarily out of view would be a more rigorous test of the existing system, which would be beneficial to the study.

The initial estimates computed are prone to error.The quality of the estimates needs to be monitored in order to determine when the estimates are good enough to be added to a database. The condition number of the covariance matrix is a good indication of the accuracy of the estimate. The use of a particle filter for bearings only initialization needs to be reconsidered and other methods, possibly linearized least squares, need to be tested for this task. However, although the condition number at the time of initialization is high as seen in Figure 4.2, it lowers within a few time steps and the estimates computed become more accurate as more measurements are accumulated.

The Joint Compatibility Test implemented in this project is not set to compute all the sets of data association matrices for more than three birds. The data association for more than three birds is therefore not always correct, leading to irregularities in the estimation process. This issue can be resolved by formulating a method to compute all permutations of data association for any number of birds.

5.2.2   Hardware Implementation

The proposed thesis is strictly based on modeling and mathematical simulation of the bird tracking system at a given site. The hardware implementation of the system has not been carried out yet. Although the physical constraints of available technology have been kept in mind while modeling the system, hardware implementation would involve addressing further, more specific details in order to attain the performance predicted in the simulation.

5.2.3   Vision based Data Association and Recognition

The system modeled in this project has cameras for sensors. The measurements used from these cameras are the computed bearings to the birds in flight which can be obtained through standard image processing techniques. Cameras provide a wealth of other information too, like color, texture and optical flow. Color information, in particular, may be used to obtain more concrete data association. The color histograms of birds can also be recorded and higher level learning techniques may be used to build a database of various species of birds seen and recognize previously viewed species, based on the unique color make-up of each species.

5.2.4   Learning Algorithms

Learning algorithms like Hidden Markov Models may be used to classify the computed position and velocity of one or more birds as unique behavior. The interactions between raptors can be recorded and identified for further study. Migratory behavior may also be classified as safe or unsafe depending on the proximity of the route from the wind farms. An intelligent system that is able to learn and identify patterns in the results obtained from tracking would provide more insight into the study of migrating raptors.

Appendix A

Appendix-A

A.1 Partial Data Association

Intermediate results of the tracking performance are presented as follows:

The tracking performance with partial data association is shown in Figure A.1. The association of bearings between cameras and from one frame to the next is unknown while the association of local estimates to each other is known.
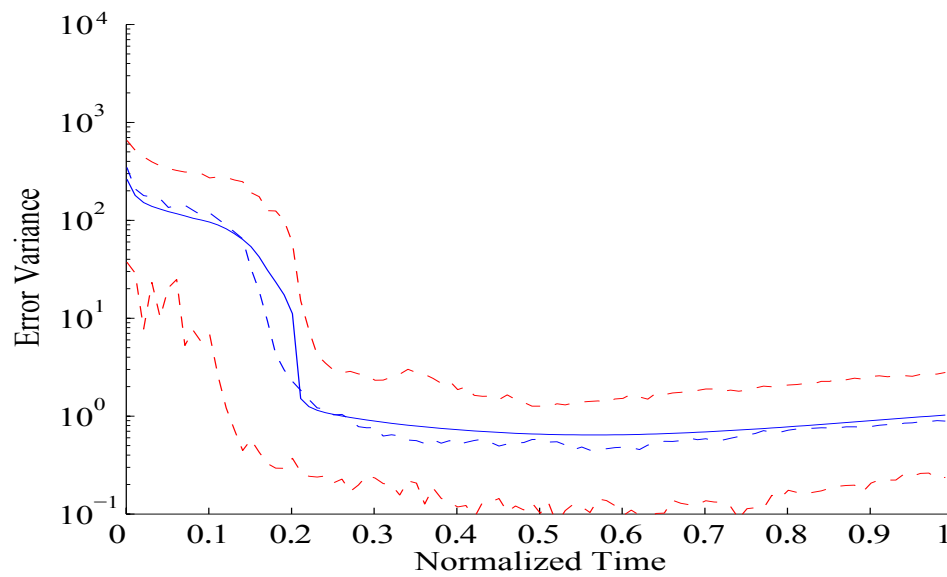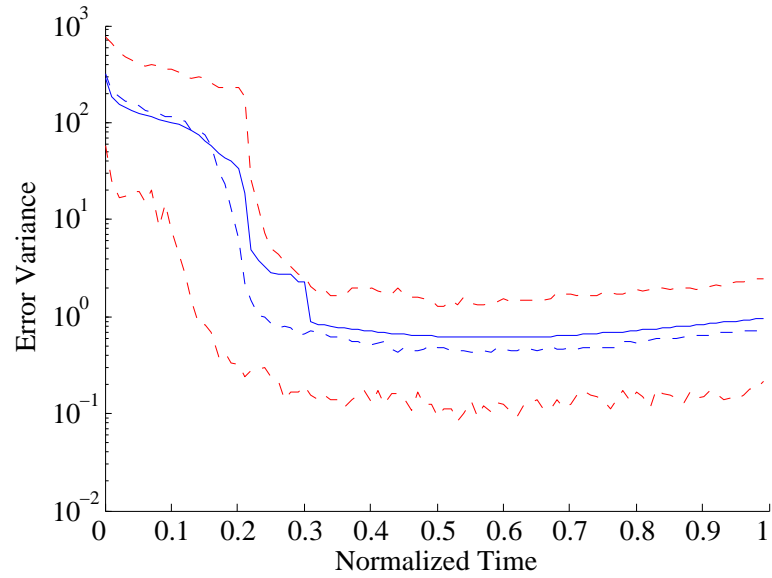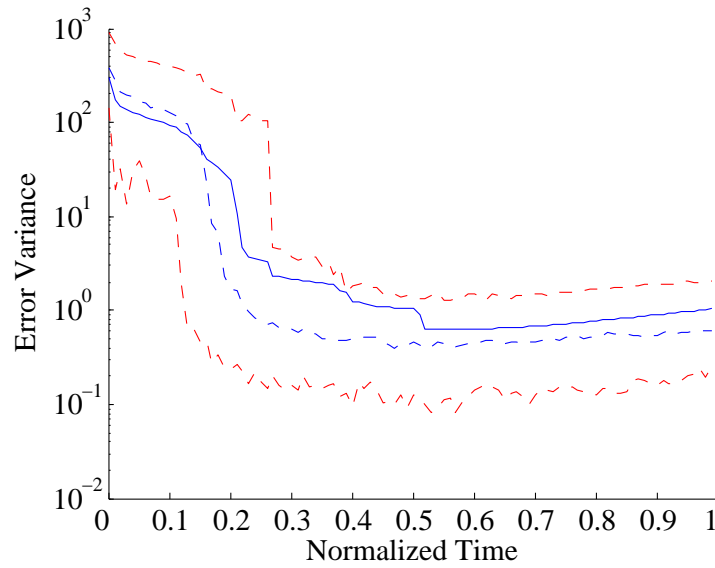
Figure A.1. Monte Carlo simulation results for systems with partially computed data association. The dashed red lines show the maximum and minimum values of the 2-norm of the true estimate error, the dashed blue line shows the mean value of the 2-norm of the true estimate error and the solid blue line is the mean value of the estimated error variance.

A.2 Data Association with increasing numbers of tracks

The ability to track more than three birds while fully computing data association for measurements as well as local estimates is shown in Figure A.2, for simulations consisting of four and five birds respectively.

(a) System tracking four birds while explicitly computing Data Association

(b) System tracking five birds while explicitly computing Data Association

Figure A.2. Monte Carlo simulation results for systems with explicitly computed data association for four and five birds. The dashed red lines show the maximum and minimum values of the 2-norm of the true estimate error, the dashed blue line shows the mean value of the 2-norm of the true estimate error and the solid blue line is the mean value of the estimated error variance.

Bibliography

[1] MOORE, F. R. (ed.) (2000) *Stopover ecology of Nearctic-Neotropical landbird migrants: habitat relations and conservation implications.*, no. 20 in Studies in Avian Biology, Cooper Ornithological Society, 496 Calle San Pablo, Camarillo, California.

[2] GOODRICH, L. "Unpublished Data," .

[3] ORLOFF, S. and A. FLANNERY (1992) *Wind Turbine Effects on Avian Activity, Habitat Use, and Mortality in Altamont Pass and Solan County Wind Resource Areas (1989-1991), Final Report, Tech. rep.*, Planning Departments of Alameda, Contra Costa and Solano Counties and the California Energy Commision, Sacrameto, CA.

[4] BARRIOS, L. and A. RODRIGUEZ (2004) "Behavioural and Environmental Correlates of Soaring-Bird Mortality at On-Shore Wind Turbines," *Journal of Applied Ecology*, **41**(1), pp. 72–81.

[5] *Tech. rep.*, Washington,D.C.

[6] "HawkWatch International," in *http://www.hawkwatch.org/home/index.php.*

[7] "Southern Cross Peregrine Project," in *http://www.frg.org/SC_PEFA.htm.* URL `http://www.frg.org/SC_PEFA.htm`

[8] KERLINGER, P. (1989) *Flight Strategies of Migrating Hawks*, University of Chicago Press.

[9] ANDREA CAVAGNA, A. O., IRENE GIARDINA (2008) "The STARFLAG handbook on collective animal behaviour: 1. Empirical Methods," in *Animal Behaviour.*

[10] CRUDELI, R. T. (2007) "A Vectorial 3D Bird Flight Monitoring System: A New Tool to Track and Manage Birds on Airports," in *FAA Worldwide Airport Technology Transfer Conference.*

[11] RAFAEL MUÑOZ-SALINAS, M. G.-S., EUGENIO AUIRRE (2007) "People Detection and Tracking using Stereo Vision and color," in *Image and Vision Computing.*

[12] .

[13] ZIVKOVIC, Z. and B. KROSE (2004) "An EM-Like Algorithm for Color-Histogram-Based Object Tracking," *cvpr*, **01**, pp. 798–803.

[14] in *http://en.wikipedia.org/wiki/Kalmanfilter.*

[15] VAN DER MERWE, R., N. DE FREITAS, A. DOUCET, and E. WAN (2001) "The Unscented Particle Filter," in *Advances in Neural Information Processing Systems 13.*
URL `citeseer.ist.psu.edu/article/vandermerwe00unscented.html`

[16] VAN DER MERWE, R. and E. WAN (2001) "The Square-Root Unscented Kalman Filter for State and Parameter-Estimation," in *IEEE International Conference on Acoustics, Speech and Signal Processing*, IEEE, Salt Lake City, UT.

[17] STENGER, B., P. R. S. MENDONA, and R. CIPOLLA (2001) "Model-Based 3D Tracking of an Articulated Hand," *cvpr*, **2**, p. 310.

[18] DOUCET, A. (1998), "On Sequential Monte Carlo Sampling Methods for Bayesian Filtering," .
URL `citeseer.ist.psu.edu/doucet00sequential.html`

[19] GUSTAFSSON, F., F. GUNNARSSON, N. BERGMAN, U. FORSSELL, J. JANSSON, R. KARLSSON, and P.-J. NORDLUND (2002) "Particle filters for positioning, navigation, and tracking," *Signal Processing, IEEE Transactions on [see also Acoustics, Speech, and Signal Processing, IEEE Transactions on]*, **50**(2), pp. 425–437.

[20] BAR-SHALOM, Y., X. R. LI, and T. KIRUBARAJAN (2001) *Estimation with Applications to Tracking and Navigiation*, Wiley Interscience.

[21] KARUPPIAH, D. R., Z. ZHU, P. SHENOY, and E. M. RISEMAN "A Fault-Tolerant Distributed Vision System Architecture for Object Tracking in a Smart Room," *Lecture Notes in Computer Science*, **2095**.

[22] KALMAN, R. E. (1960) "A New Approach to Linear Filtering and Prediction Problems," *Transactions of the ASME Journal of Basic Engineering*, (82 (Series D)), pp. 35–45.

[23] SEBASTIAN THRUN, W. B. and D. FOX (2006) *Probabilistic Robotics*, The MIT Press.

[24] SIMON, D. (2006) *Optimal State Estimation*, Wiley-Interscience.

[25] BAILEY, T. (2003) "Constrained Initialisation for Bearing-Only SLAM," in *IEEE International Conference on Robotics and Automation (ICRA)*, IEEE, Taipei, Taiwan.

[26] FITZGIBBONS, T. and E. NEBOT (2002) "Bearing Only SLAM using Colour-based Feature Tracking," in *2002 Australasian Conference on Robotics and Automation*, Auckland, New Zealand.

[27] MONTESANO, L., J. GASPAR, J. SANTOS-VICTOR, and L. MONTANO (2005) "Fusing Vision-Based Bearing Measurements and Motion to Localize Pairs of Robots," in *International Conference on Robotics and Automation*, Barcelona, Spain.

[28] DAVISON, A. J. (2003) "Real-Time Simultaneous Localisation and Mapping with a Single Camera," in *International Conference on Computer Vision*, Nice, France.

[29] I ORTEGA, J. S., T. LEMAIRE, M. DECY, S. LACROIX, and A. MONIN (2005) "Delayed vs Undelayed Landmark Initialization for Bearing Only SLAM," in *Workshop on Simulateous Localisation and Mapping, International Conference on Robotics and Automation*, Barcelona, Spain.

[30] KWOK, N. M. and G. DISSANAYAKE (2004) "An Efficient Multiple Hypothesis Filter for Bearing-Only SLAM," in *Interational Conference on Intelligent Robots and Systems*, Sendai, Japan.

[31] NIERA, J. and J. TARDOS (2001) "Data Association in Stochastic Mapping Using the Joint Compatibility Test," *IEEE TRANSACTIONS ON ROBOTICS AND AUTOMATION*, **17**(6), pp. 890–897.

[32] JULIER, S., J. UHLMANN, and H. F. DURRANT-WHYTE (2000) "A New Method for the Nonlinear Transformation of Means and Covariances in Filters and Estimators," *IEEE Transactions on Automatic Control*, **45**(3), pp. 477–482.

[33] HASHEMIPOUR, H., S. ROY, and A. LAUB (1988) "Decentralized Structures for Parallel Kalman Filtering," in *IEEE Transactions on Automatic Control*, vol. 33, pp. 88–94.