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Extracting Movement Patterns Using Fuzzy and Neuro-fuzzy Approaches

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EXTRACTING MOVEMENT PATTERNS

USING FUZZY AND NEURO-FUZZY APPROACHES

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An Abstract of the Thesis Presented
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Several applications generate large volumes of data on movements including vehicle navigation, fleet management, wildlife tracking and in the near future cell phone tracking. Such applications require support to manage the growing volumes of movement data.

Understanding how an object moves in space and time is fundamental to the development of an appropriate movement model of the object. Many objects are dynamic and their positions change with time. The ability to reason about the changing positions of moving objects over time thus becomes crucial. Explanations on movements of an object require descriptions of the patterns they exhibit over space and time. Every moving object exhibits a wide range of patterns some of which repeat but not exactly over space and time such as an animal foraging or a delivery truck moving about a city. Even though movement patterns are not exactly the same, they are not completely different. Moving objects may move on the same or nearly similar paths and visit the same locations over time.

This thesis addresses the identification of repeat movement patterns from large volumes of data. These are represented as higher-level movement structures referred to as movement signatures. Movement signatures are defined as collections of patterns that objects demonstrate in their sequences of movements. Signatures have a spatial structure that includes dominant or frequently visited locations and paths and a spatio-temporal structure that associates a temporal pattern with the spatial patterns. This thesis demonstrates the extraction of movement signatures from sets of movement observations using fuzzy and Neuro-fuzzy methodologies. Identification of movement signatures and definition of their attributes provides summary level information for modeling and reasoning about moving objects.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

Most real world phenomena are dynamic and the positions of many objects change with time. The ability to reason about the changing positions of moving objects thus becomes crucial. The phenomenon of movement arises whenever the same object occupies different positions in space at different times (Galton, 1995). Movements are complex types of spatio-temporal change. Although movements occur continuously, people often perceive them discretely. Movement is the key to contemporary life. People, animals, objects and ideas move in space and time, always interacting with each other and with their environment, creating a highly dynamic system.

We define movement as comprising a change in the location (i.e., a translation) or in the orientation (i.e., a rotation) of a point object over time. We categorize change to an object's boundary as shape change (Agouris et al., 2000a) and distinguish it from movement. This separation distinguishes important behavioral differences between objects, for example lakes and cars. Lakes frequently shrink and expand, but are not subject to rotation or translation and hence do not change position (except in a possible catastrophic event). Cars, on the other hand, frequently change their position, but do not change their boundary configuration or shape. Objects may exhibit both types of change: movement (Beard and Palancıoğlu, 2000) and boundary reconfiguration (Agouris et al., 2000a).

Real world phenomena are capable of voluntary and involuntary movement. Some objects move continuously and some intermittently, and some in regular time

dependent patterns (Yuan, 1998). For example some objects are frequently at rest such as people and animals, some objects move in discontinuous steps (periods of continuous movement followed by no movement) such as cars and ships, and some objects exhibit continuous movement such as oil spills, wind, floods, glaciers, and desert erosion.

Modeling moving objects has become a topic of recent interest, but it is still in its infancy. Modeling of moving objects has turned out to be a multi-disciplinary research issue involving disciplines like linguistics, cognitive science, physics, robotics, geography, computer science, and mathematics. Research activities during recent years have addressed representation and modeling of moving objects within GIS environments. Most research in this area focuses on tracking the movement of a single object, i.e., the trajectory of an object over a period of time. There is an increasing need to represent the paths of moving objects over extended time periods and the relative spatio-temporal relations among multiple moving objects (Partsinevelos et al., 2000; Stefanidis et al., 2000). Models of moving objects should be capable of expressing a set of spatio-temporal topological and orientation (direction and distance) relations among them. The representation of these relationships may be expressed qualitatively as well as quantitatively (using the coordinates) both to save space and to simplify reasoning.

The research presented in this thesis focuses on analytical methods suited for the exploration of movement of discrete objects. The term 'point objects' is used in this research as a generalization of very different phenomena, such as trucks, airplanes, animals or human beings.

1.1 Motivation

Understanding how an object moves in space and time is fundamental to the development of an appropriate movement model of the object. Without including movements of objects, it is difficult to model and reason about the dynamics of the real world. There are many types of moving objects such as taxis, ships, packages, and individuals and their positions change with time. Moving objects are frequently modeled as discretely moving points (i.e., point objects at rest at a certain location for a time interval and then moving instantaneously). The ability to model, analyze, and reason about the changing positions of moving objects over time thus becomes crucial. The increasing demand for models that are capable of dealing with the movements of objects highlights the need for research in this particular area. A system with the ability to model, analyze, and reason about movements of objects is an important asset and requirement in several applications. Such applications include vehicle navigation, fleet management, wildlife tracking, emergency dispatch, disease monitoring, and military applications to name a few. In all these applications there is a need to efficiently answer questions about moving objects such as where they are at a specific time, where they have been in the past, where they will be in the future.

However, we need observations on the movements of objects to model, analyze, and reason about them. Observations refer to any measurements that capture the position of objects at particular times. Unless we have observations that are almost continuous (i.e., video stream, GPS observations) we cannot account for every instant of a movement. Knowledge of movement is limited by the ability to observe it. Complete knowledge of any particular movement is impossible, but movements can be detected,

stored, modeled and analyzed with some degree of accuracy. Enhanced data collection technologies such as high resolution satellite imagery, videogrammetry, and GPS in combination with wireless communications are rapidly increasing the feasibility of obtaining information on moving objects and fueling new research and development in this area. In addition, development of new and more powerful techniques and tools in computer animation, three-dimensional modeling, visualization, database systems, and query languages provide efficient use of the observation data in modeling and reasoning about moving objects.

Typically, observations obtained on the movements of an object from various sources have a similar format that includes the coordinates of a set of positions visited by an object and a time. Given a large number of observations, one might want to identify particular meaning or structure in the spatial and spatio-temporal extent that reveals movement patterns of the corresponding object such as the locations frequently visited or paths frequently taken by the object over time. Explanations on movements of objects require descriptions of the patterns they exhibit over space and time.

1.1.1 Fuzziness and Uncertainty in Moving Objects

Many spatio-temporal applications need to model real world phenomena not simply by crisply defined objects but rather through vague concepts that accomadate indeterminate positions and/or boundaries that change and/or move over time (Burrough, 1996; Frank, 1996). This thesis emphasizes a special kind of vagueness called fuzziness. Fuzziness captures the characteristic of many spatio-temporal phenomena, which do not have sharp boundaries or exact positions or whose boundaries or positions cannot be precisely determined such as oil spills and moving vehicles.

Many moving object applications need support to handle uncertainty, subjectivity, imprecision, and ambiguity related to movements of objects in the context of spatio-temporal modeling and reasoning. Spatio-temporal queries related to moving objects need to deal with the uncertainties embedded in the object's movements. Human decision-making and reasoning in general and in movement modeling in particular use qualitative knowledge or linguistic information on a daily basis when reasoning about movements of objects. In many situations humans use linguistic information more easily than numerical information. However it is very difficult to formulate a suitable mathematical model of this reasoning process. Therefore, one needs to use methods that are capable of handling these uncertainties.

Currently, there have been efforts to incorporate uncertainties related with spatio-temporal data in modeling and decision support by using fuzzy logic approaches (Altman, 1994; Stefanakis et al., 1999; Vazirgiannis, 2000; Wang et al., 1990; Wang and Adelson , 1994). This thesis proposes the use of fuzzy methods to enhance modeling and hence reasoning about movements of objects. Fuzzy methods are incorporated in the approach to address the presence of incomplete and imprecise information to represent a degree of impression in the summary description of movement patterns.

1.1.2 Why Use a Fuzzy Set Approach?

A key motivation for the use of fuzzy sets is the ability to handle uncertainty. Traditionally, uncertainty is considered undesirable and one tries to reduce it as much as possible in order to come to precise conclusions. However, all perceptions of the real world are imprecise and uncertain, and our natural language has evolved to represent and

communicate this imprecision. Despite the vagueness in linguistic descriptions, valuable information can be conveyed linguistically provided one can deal with the imprecision.

The benefits of the fuzzy approach stem from the following aspects:

- Fuzzy systems are able to capture and deal with meanings of linguistic expressions and conceptually such systems are easy to understand.
- Fuzzy systems are able to blend different types of quantitative and qualitative information.
- Because of the ability of fuzzy logic to incorporate qualitative information, fuzzy systems are able to adequately model processes where human reasoning and decision-making are involved.
- Fuzzy systems can be built on top of the experience of experts.

Cognitive science has shown that humans often use fuzzy logic methods to reason about events in their daily life. In many real world situations, humans have the ability to reason about movements of objects using vague variables and linking different objectives. In many problems, fuzzy set theory is an approach that is much closer to real human observation, reasoning and decision making than traditional statistical approaches, such as probability theory (Hoogendoorn et al., 1998). For humans, navigation in space can be handled by using approximate values and constraints (i.e., weather and road conditions). People draw on previous experience to decide on the most appropriate path to choose among different options to travel between two locations. For example, a person who travels between home and work can predict certain information related to the path such as how long this path might take according to the time of day and weather.

Computers are especially incompetent in dealing with the vagueness and imprecision that is part of everyday life. People, however, can handle most of these problems, dealing with the imprecision, to the extent that is sufficient in most cases. Humans can reason in an appropriate way and accommodate the imprecision in a manner that allows solving complex problems. According to one of the major principles in fuzzy set theory, the ability of humans to deal with uncertainty is ultimately connected to their ability to solve complex problems within a reasonable amount of time (Dutta, 1990). That is, allowing more uncertainty tends to reduce complexity, increase credibility in the resulting model and allow a computationally feasible solution. The main area of application of fuzzy systems is the vast majority of complex systems where relatively few data exist, where only imprecise, uncertain or ambiguous information is available, or where expert knowledge is expressed vaguely in natural language.

Fuzzy logic methodologies (Zadeh, 1979) provide a framework for the modeling and handling of the uncertainties that are related to the positions and paths of moving objects. Instead of numerical descriptions for the representation of positions and paths of moving objects, fuzzy values can be assigned. For example, assume the statement that "the package was picked up from location A and delivered to location B". There is uncertainty in this statement related to the perception of the pick up and delivery locations and the path connecting them. The perceived locations and the path can be represented with fuzzy values based on movement observations.

Several factors have encouraged the consideration of fuzzy methodologies for movement modeling including but not limited to the followings:

- Imprecise and Uncertain Data
- Complete and accurate description of movements is impossible. Many reasons including cost, time and difficulty in collecting precise data about movements of objects necessitates the use of fuzzy reasoning.
- Complexity

  Movements of objects can be enormously complex.
- Representation Expressivity

  Certain situations, in particular movements, are more conveniently described by linguistic variables than by numerical variables.
- Reasoning Methodologies

  Limited reasoning methods with uncertain and imprecise data on movements of objects are also among the reasons for the use of fuzzy methodologies.

Along with these, the use of fuzzy sets is beneficial to a number of applications in movement modeling including:

- Identifying moving objects (i.e., vehicle, animal),
- Predicting movement patterns of objects (i.e., frequently visited locations and used paths by objects),
- Reasoning and decision-making (i.e., estimating the locations of a moving object over time).

1.2 Problem Statement

Current information systems have been documented as lacking (Al-Taha, 1992; Fischer, 1994; Laurini and Thompson, 1992; Leung and Leung, 1993; Stefanakis and Sellis, 1996; Stefanakis and Sellis, 1997; Stefanakis et al., 1999):

- Appropriate logical foundations for handling the uncertainty of data
- Modeling and reasoning functionalities
- Support for the temporal dimension
- Techniques for indexing and querying dynamic data
- Intelligence and ability to make predictions under uncertain situations

This thesis focuses on the first two limitations mentioned above in the specific context of moving objects. Several of these deficiencies have been and continue to be addressed in (Al-Taha, 1992; Armstrong, 1988; Egenhofer and Golledge, 1997; Langran, 1988; Peuquet, 1994; Saltenis et al., 2000; Wolfson et al., 1998; Worboys, 2001; Yuan, 1998).

The problems related to modeling movements of objects are identified in this thesis as follows:

- Many objects are dynamic and their positions change with time.

  Modeling the movements of an object requires at least the integration of changes in spatial and temporal dimensions. Similarly changes in the environment through which the objects are moving adds to the complexity.

- Every moving object exhibits a wide range of patterns some of which repeat but not exactly over space and time.

  Even though movement patterns are not exactly the same, they are also not completely different. Moving objects may move on the same or nearly similar paths and visit the same locations over time such a home and work locations visited by an individual.

- Explanations on movements of an object require the description of the patterns it exhibits over space and time.

  Availability of observation data, which may be sparse, makes it difficult to model and reason about an object's movement patterns such as locations visited and paths used by the object.

- Due to the volume of data, there is an increasing need to provide data summarization, identify important patterns, and reason upon the findings.

  It is difficult to store exact knowledge on the movement of objects. As the volume of data collected and stored in databases grows, especially in moving object applications, there is an increasing need to provide data summarization, identify important patterns, and reason upon the findings.

1.3 Objectives and Hypothesis

Approximate modeling and reasoning methods have been used with demonstrably good results in human perception and cognition. How the human mind performs such complex modeling and reasoning tasks easily is an important research area (Dutta, 1988; Gaines, 1976; Stefanakis et al., 1996). The proposed fuzzy and neuro-fuzzy approaches in the thesis are a step to incorporate the similar modeling and reasoning methodologies that are used by humans.

This thesis develops a methodology for modeling movements of objects and handling uncertainties embedded in these movements using both numeric and linguistic movement information. The focus is on devising a suitable computational framework for representing general movement behaviors of objects given imprecise and incomplete numeric and linguistic information about their movement in space over time.

The proposed approach addresses the ability of information systems to answer questions about moving objects such as where they have been in the past, where they are now, or where they may be at a specific time by using their expected movement patterns. The methodology incorporates three pieces of information: movement profiles, observations, and movement signatures among which the development of movement signature is the specific focus.

Movement profiles provide information on general constraints on movements of objects. They identify constraints on the movement of a class of objects. Observations provide essential information for the computation of a moving object's position. Observations are defined as sightings of a particular object at specific locations and times. Observations refer to any measurements that capture the location of objects at particular times. General knowledge about movement patterns of objects can be acquired by analyzing a set of movement observations. Movements of objects over space and time can be modeled based on a set of observations. A **movement signature** is a summary of a set of movement observations on an object over some period of time. Movement signatures are higher-level abstractions of observations that capture dominant patterns of a moving object over time.

The hypothesis of this thesis is:

"A set of position observations on a moving object reveal high-level movement patterns over space and time."

The main objectives of this thesis are to:

- identify and formalize elements of movement,
- investigate movement patterns of an individual object,
- define and represent movement patterns at higher levels of abstraction through movement signatures,
- extract, and formalize spatial and spatio-temporal movement signatures,
- develop methodologies to extract movement signatures,
- classify and order movement signatures.

1.4 Research Questions

The major questions addressed by this thesis include:

- how to define movement signatures?

  Patterns of an individual (i.e., a car) such as possible locations and paths can be obtained from a set of movement observations. These movement patterns are summarized in the form of signatures.

- how to obtain and represent movement signatures?

  Both numeric and linguistic observation can be employed in obtaining movement signatures of an object. Representation methods need to reflect the more abstract (less precise) form of signature.

- how to summarize movement observations?

  Due to the volume of movement data, there is a need to provide data summarization to identify important movement patterns. Implementation of data mining methods needs to be considered.

- how to employ fuzzy and neuro-fuzzy methods to extract signatures?

Methods of implementing fuzzy and neuro-fuzzy methods in extracting movement signatures from a set of movement observations need to be developed and evaluated.

1.5 Scope of Research

This thesis does not address:

- modeling motion of objects, which describes continuous movements of objects usually obtained as video sequences.
- modeling movements of all types of objects,
- detecting, storing, and indexing movements of an objects,
- developing precise models of movements,
- modeling physical characteristics of moving objects such as speed and mobility,
- modeling the constraints on objects,
- developing movement signatures of an object using all its movement parameters (i.e., locations, directions, distances, speeds), but a set of movement parameters that are locations that they occupy, time of occupying each location, and number of visits to each locations.

1.6 Proposed Contributions

Proposed contributions of this thesis can be outlined as follow:

- Introducing the concept of "movement signatures",

  The concept of "movement signatures" is introduced as a component for use in modeling moving objects. Methods to identify and formalize elements of movement signatures of an object will be the main contribution of this thesis.

- Demonstrating an approach to define and extract movement signatures,

  Meaningful movement patterns of an object can be summarized in the form of movement signatures in both spatially and temporally. Methods to define and extract movement signatures from a set of observations are vital for modeling and reasoning about moving objects.

- Implementing fuzzy and neuro-fuzzy methods in extracting movement signatures.

  Fuzzy and neuro-fuzzy methodologies can be implemented as a novel way of extracting movement signatures and handling uncertainties related to movements of objects. The implementation of fuzzy and neuro-fuzzy methods in modeling movements will be another major contribution of this thesis.

1.7 Intended Audience

This thesis is intended for researchers interested in exploring new approaches in geographic information systems in particular to model moving objects and uncertainties related to them. Its intended audience includes researchers concerned with alternative methods to handle uncertainties in real world scenarios, geographers trying to model the movements of objects, cognitive scientists interested in reasoning using imprecise and uncertain data, database specialists looking for ways to assess the importance and use of fuzzy methodologies, and researchers concerned with spatio-temporal modeling.

1.8 Organization of Thesis

The remainder is this thesis is organized as follows.

Chapter 2 reviews existing spatio-temporal modeling approaches and presents modeling and reasoning issues related with moving objects. In addition, it reviews the concepts of fuzzy logic and uncertainty.

Chapter 3 discusses the proposed approach to model moving objects and the concept of movement signatures.

Chapter 4 explains how to model locations of moving objects to obtain spatial location signatures.

Chapter 5 demonstrates an approach to extract spatio-temporal location and path signatures of moving objects.

Chapter 6 summarizes the thesis, identifies contributions, and highlights possible further research based on the findings of this thesis.

Chapter 2

BACKGROUND

Modeling the dynamics of the world requires at least the integration of space, time, and movement (Galton, 1993). Today's Geographic Information System (GIS) data models have not fulfilled the requirements for integrating space and time. Until now, space has been the focus of models of geographic phenomena. The GIS data models focus on modeling and reasoning about space. Although time in GIS has been a research topic over the last ten years (Egenhofer and Golledge, 1997; Langran, 1988; Peuquet, 1994), models for GISs still treat space and time separately and support only a world that exists in the present or as a collection of temporal snapshots. Incorporation of the dynamics of geographic phenomena within a GIS is only available in the most rudimentary fashion.

GIS should be able to represent and reason about dynamic geographic phenomena in both space and time. Integration of space and time for spatio-temporal analysis and reasoning has gained significant attention (Langran, 1992b; Peuquet, 1999; Worboys, 1998). There has been considerable research in modeling, representing, and reasoning about space and time resulting in different forms of temporal (Allen, 1984) and spatial logic (Egenhofer and Franzosa, 1991; Randell et al., 1992). An integrated logic of space, time, and motion was presented by (Galton, 1993).

As space and time dimensions interact with each other, changes occur on geographic phenomena. Explanations of geographic phenomena often require the description of these changes. Without including changes, especially movements of

geographic phenomena, it is impossible to model and reason about the dynamics of the real world. Understanding how geographic objects change over time is fundamental to the development of appropriate models of the real world (Hornsby, 1999). We identify spatio-temporal changes as the differences between the states of dynamic geographic phenomena over time. Examples of spatio-temporal changes include changes in the boundary of a country, in the position of a car, and in the path of a wild fire. People are good at detecting changes through visual observations from such sources as satellite images, photographs, and videos. Collectively, these heterogeneous observations form a rich source for identifying changes. People observe various types of changes in their daily lives such as movements and they have no difficulty in understanding and reasoning about them. However, the implementation of models of spatio-temporal change within information systems has yet to be realized. Currently, data stored in a GIS can be updated, but records of changes are not explicitly maintained.

The increasing demand for information systems that are capable of dealing with scenarios of change emphasizes the need for research in this particular area (Hornsby and Egenhofer, 1997). The concept of change must be formalized in order to create spatio-temporal models for the dynamic world. Spatio-temporal models have been developed (Erwig et al., 1997; Hornsby, 1999; Langran, 1989; Langran, 1992a; Peuquet and Wentz, 1994; Sistla et al., 1997), however, they do not deal with all aspects of dynamic geographic phenomena effectively. In order to develop a meaningful model of change, it is paramount to analyze its ontological foundations.

Spatio-temporal systems must be designed to deal with changes of spatial and temporal properties. Beard and Palancıoğlu (2000) identified three components of

change: boundary redefinition (Agouris et al., 2000a), thematic state change, and movement. The main focus of this research is on the third component: movement and uncertainties related to it. We seek to improve the understanding of the concept of movement for geographic phenomena and its representation in information systems. As one of the crucial components of dynamic geographic phenomena and change, the concept of movement has been studied under various names, such as migration, motion, and transportation in different scientific fields. In this thesis, we use the term movement.

2.1 Spatio-temporal Modeling

An object that occupies a position in a space is referred to as a 'spatial object'. An object whose position may change over time is called a 'spatio-temporal object' (Renolen, 1998). In addition, an object that is able to move over time and change its position is referred to as a moving object.

A data model has been defined as the structure that describes types of data objects and a framework for organizing and managing them. It has three major components (Yuan, 1997): a set of object types, a set of operations, and a set of integrity rules. A spatio-temporal data model can be defined as a data model that is designed for modeling the real world where objects change their positions and shapes over time (Susumu and Makinouchi, 1999). Currently, spatio-temporal models assume that objects have crisp boundaries, precisely defined relationships with other objects, and accurately measured positions in space with error-free representation. However, in the real world, objects have vague boundaries, relationships, and positions. In addition, moving objects have changing relationships and positions that might not be exactly known at all times (i.e., due to lack of observations and knowledge). In other words moving objects have uncertainties and

vagueness related with their boundaries, relationships, and positions (Pfoser and Tryfona, 2000). Several spatio-temporal data models have been presented that record spatial and temporal changes (Hazelton, 1992; Kelmelis, 1991; Langran, 1992b; Peuquet and Duan, 1995). Peuquet (1999) identified spatio-temporal data models in four categories a) Location-based b) Entity-based c) Time-based and d) combined approaches.

The following categorization was presented in (Renolen, 1995):

- One of the basic spatio-temporal models is the snapshot model (Figure 2.1). The disadvantage of this model is that it supports a world that exists in the present or as a collection of temporal snapshots. The snapshot model is unable to identify changes explicitly (Armstrong, 1988; Langran, 1988; Peuquet and Duan, 1995).

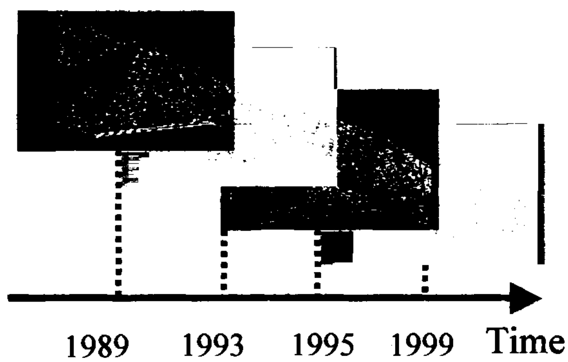


Figure 2.1: The snapshot model.

- Another simple approach is the data model based on time-stamping, that is, assigning time stamps for the creation and cessation time of every object (Galetto and Viola, 1994; Hunter and Williamson, 1990). This approach tracks different versions of the same object over several non-related tuples within the same table. This makes it difficult to determine the history of one single object (Montgomery, 1995). There have been different approaches proposed to solve this problem including implementing an object-oriented model called a "temporal change

object (Ramachandran et al., 1994)", which assigns references to the past, future and current versions of the same object, organizing the versions of an object into time sequences (Segev and Shoshani, 1993).

- The space-time composite model, a vector model, was proposed by Langran and Chrisman (1988). However, this approach also has some redundancy since two objects may have full or partial common histories assigned to them. Although, this approach is promising, its indexing method and structure of the data needs to be tested in order to deal with large data sets.
- As an alternative to the snapshot models, event-oriented or time-based models such as "amendment vector approach" and "event-oriented spatio-temporal data model-ESTDM" have been suggested (Langran and Chrisman, 1988); (Peuquet and Duan, 1995); (Claramunt and Thériault, 1995) in order to identify individual changes or events to the data set in between the snapshots. Despite some of the advantages of these approaches, they need to be investigated and tested further.
- In addition, object-oriented data models have been implemented (Egenhofer and Frank, 1992; Worboys, 1992). In these models, all versions of the same object are embedded into one single entity and time is usually represented as one of the dimensions in 3D or 4D space.

A challenge in spatio-temporal modeling comes from incorporating "space" and "time" dimensions in the same database. Spatial databases (Guting, 1994; Shekar et al., 1999) contain records on space varying phenomena. Temporal databases (Jensen and Snodgrass, 1999; Snodgrass and Ahn, 1985) are characterized as managing records of time varying information. The management of information on phenomena that have both

time and space varying patterns are handled by spatio-temporal databases. Research in spatio-temporal databases has taken the form of both temporal extensions to spatial databases and spatial extensions to temporal databases.

Modeling, indexing, and query languages for spatio-temporal data have all received attention. Langran (1992b) addressed a set of practical issues concerned with data representation, incremental updates, and system longevity. Langran (1988) examined the concept of combined spatial and temporal dimensions and suggested that dimensional dominance must be determined for the optimization of data and the algorithms. Snodgrass and Ahn (1985) described the need to consider the evolution of spatial objects in addition to retroactive or post active changes.

Temporal indexing often includes two aspects of time, valid time and transaction time. When both times are included this is referred to as a bitemporal database (Jensen and Snodgrass, 1999). Full spatio-temporal support is assumed to include these two temporal aspects as well as two or three spatial dimensions. Spatio-temporal indexing raises significant challenges. Spatio-temporal indexing has typically used one of two approaches (Saltenis and Jensen, 1999): 1) overlapping index structures that index spatial objects at different times or 2) the addition of time as another dimension to an existing spatial index.

Query languages have been the subjects of related research. Spatial query languages (Egenhofer, 1994; Shekar et al., 1999) supporting various spatial operations have been developed. Likewise temporal query languages have been evolving (Snodgrass, 1987). Spatio-temporal query language extensions need to develop in parallel with these independent spatial and temporal query language developments.

2.2 Modeling Moving Objects

Management of information about moving objects requires database support and there has been substantial research activity in this area recently. Relevant research covers spatio-temporal databases, moving object databases (Erwig et al., 1997; Wolfson et al., 1999; Wolfson et al., 1998), spatio-temporal indexing (Saltenis and Jensen, 1999), indexes for moving objects (Kollios et al., 1999; Saltenis et al., 2000), representations of the uncertainty of moving objects (Moreira et al., 1999; Pfoser and Jensen, 1999), and ontological considerations for movement and moving objects (Galton, 1995).

Existing databases are incapable of handling continuously changing data, such as the position of moving objects. Sistla et al. (1997) proposed a model to solve this problem by representing the position of moving objects as a function of time. In this model, a higher level of data abstraction that treats an object's motion vector as an attribute of the object is considered. Moving objects fall directly within the purview of spatio-temporal databases. Moving object databases are a specialization of spatio-temporal databases for discrete and continuously varying spatial and temporal information. A continuous model for continuous movement may be desirable but not practical in the near term. Data observation streams are not fully continuous and there are difficulties in storing and indexing continuous movements.

Wolfson et al. (1999) identified a set of capabilities for managing moving objects that are not provided by current databases. These deficiencies include location modeling, query support, indexing, and uncertainty issues. Within a conventional relational database, the position of a moving object may be recorded and periodically updated. The assumption however is that the position of the object is constant between updates.

Updates to an object's position can be made at frequent intervals but continuous updates of locations are not feasible. Additionally frequent updates create performance problems if they require frequent updates of the index in response to the updated positions. In terms of query languages, traditional query languages such as SQL are not satisfactory for spatio-temporal range and spatio-temporal join queries and can be particularly problematic for moving object queries. Moving object queries also need to accommodate semantics for uncertainty. Since frequent updates to an object's location can be costly and because position is assumed to be constant between periodic updates, query responses from the database will not accurately reflect a moving object's position. Moreira et al. (1999) have proposed superset and subset semantics as one approach to address the uncertainty in queries regarding moving object trajectories.

Several current research activities (Saltenis et al., 2000; Wolfson et al., 1999) address enhancements for support of moving object information. Wolfson et al. (1999) incorporated the notion of a dynamic attribute, one whose value is updated continuously as time passes along with incorporating a higher level data abstraction referred to as an object's motion plan. The dynamic attribute is only explicitly updated in response to changes in the motion plan. Saltenis et al. (2000) proposed a time parameterized R–tree which indexes the current and anticipated future positions of moving objects.

Erwig et al. (1999) proposed a model for moving objects based on the abstract data types, which are namely moving points and regions (Figure 2.2), along with a set of operations on such entities. A value of type moving point representing a position as a function of time can be described as a curve in the 3-D space (x, y, t). In addition, a value of type moving region can be represented as a set of volumes in 3-D space (x, y, t). Erwig

et al. (1999) also introduced an algebra for the types: moving points and moving regions, which uses operations namely mdistance, visits, trajectory, length, minvalue, maxvalue, attime, mintime, and maxtime. He suggested that these data types and operations could be integrated into Database Management Systems (DBMS) or query languages to provide a complete data model and query language.

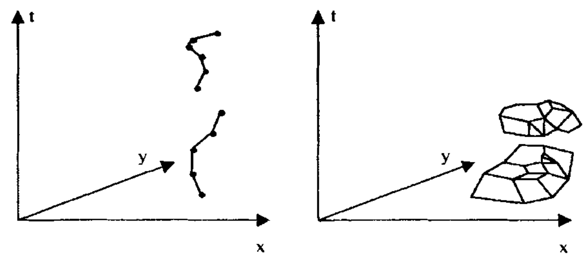


Figure 2.2: Discrete representations for moving points and moving regions.

Recently, a model for moving objects in a multimedia scene has been proposed by Nabil et al. (1997). In this approach, moving objects are represented with their trajectories, as snapshots. In addition, there have been approaches that employ Voronoi diagrams to model continuously moving objects (Albers and Roos, 1992; Fu and Lee, 1991; Guibas et al., 1991).

2.2.1 Analyzing and Summarizing Movements

Hägerstrand (1970) introduced the concept of a "space-time path" to illustrate how a person navigates his or her way through the spatial-temporal environment. Later, Miller (Miller, 1991) discussed using the concept of a space-time path for modeling accessibility within a GIS framework. In addition, recently the notion of "geospatial lifeline" as a special class of spatiotemporal data has been introduced in (Mark and Egenhofer, 1998). The notion of geospatial lifelines can be seen as a natural operational extension from the concept of space-time path. A geospatial lifeline is a continuous set of

positions occupied by an object in geographic space over some time period (Mark and Egenhofer, 1998). Geospatial lifelines that capture an individual's movement over space and time is a powerful concept in dealing with a wide range of practical problems across in many disciplines. The geospatial lifelines were used to model movements of objects (Ramaswamy, 2000). "Lifeline beads", which are a particular form of a geospatial lifeline that model the set of all possible locations an object could visit while moving between locations is developed in (Ramaswamy, 2001). Intersections of lifeline beads reveal more detailed information about the properties of objects' movements and provide more powerful support for query processing. These intersections can be used in analyzing movement patterns of multiple objects.

A framework for modeling the movement of objects or individuals over multiple granularities is introduced in (Hornsby, 2000b; Hornsby and Egenhofer, 2002). A set of operations is developed in (Hornsby, 2000a) to summarize spatio-temporal data related to objects into views at a coarser temporal detail. This paper discussed methods for creating summaries of spatio-temporal data, assisting users to retrieve information and make queries in a more effective way.

Imfeld (2000) has proposed a technique in order to analyze spatio-temporal behaviors in the movements of animals by extending the radial distance functions, which can also be used to model human movement behavior. A number of generic operations such as identification of attribute values at specific times/locations, max/min and start/stop times for spatio-temporal analysis were presented recently in (Erwig et al., 1999) that can be used to assist in making summaries of movement data.

In addition Forer (1998) suggested plotting various spatial entities as solid cubic cells occupying spatial and temporal dimensions. The model shows the individual as a consumer of time space. Individuals will form a single wandering line that will be constant in size but move spatially through time.

Unless we have observations that are almost continuous (i.e., video stream, GPS observations) we cannot account for every instant of a movement. We know that movements in the real world have duration. Descriptions of movement are often limited to the actual observations that we use to detect them and the interpolation methods (Chiyokura, 1986; Franke and Nielson, 1990; Mountain and Raper, 2001b), which are available. By accumulating observations about moving objects we can describe their trajectory. Analysis of the trajectory parameters provides us with tools for understanding behaviors of moving objects.

Behaviors of moving objects can be obtained by summarizing video datasets (Adelson and Wang, 1994; Li et al., 1997; Vasconcelos and Lippman, 1998). An approach to summarize video datasets by analyzing the trajectories of objects within them is introduced by Stefanidis et al. (2000). They obtained movements by tracing objects in this 3-D (x, y, t) space. These trajectories are the basic elements upon which the proposed summarization scheme is based.

Detection and generalization of spatio-temporal trajectories from video datasets or motion imagery (Li et al., 1997; Partsinevelos, 2002; Vasconcelos and Lippman, 1998) is an important research topic in movement modeling. The concept of a spatiotemporal helix as a concise representation of spatiotemporal events, modeling their path in space and the variations of their outline is introduced in (Partsinevelos, 2002). A set of

algorithms was developed to support the automated generation of spatiotemporal helixes. These spatiotemporal helixes can be used in spatio-temporal analysis of movements of objects.

Movements of objects and their movement behaviors repeat periodically in space (x, y) and time (t). Identifying repeated movements and behaviors of an object is a strong cue for object and movement recognition (Boyd and Little, 1997; Goddard, 1997). In addition, periodic movement can also aid in tracking objects (Cutler and Davis, 1998). Furthermore, the periodic movement of people can be used to recognize individuals (Little and Boyd, 1998). Signatures obtained from periodic movements are referred to as the systematic signatures of moving objects.

2.2.2 Reasoning About Moving Objects

Spatio-temporal reasoning is a part of humans' daily lives and yet people rarely notice it. Spatio-temporal reasoning is a new research area and current methods to infer spatio-temporal information are limited (Altman, 1994; Dragicevic and Marceau, 1999; Stefanakis et al., 1996). Cognitive theory assumes that humans' mundane activities and experiences in space over time are integrated and further used metaphorically to reason in other circumstances (Anderson, 1983; Eisenkolb et al., 1997; Hirtle and MacEachren, 1998; Mark, 1999). Human perception and experience should be explored to guide the construction of reasoning methodologies in spatio-temporal systems. (Egenhofer and Golledge, 1997). Existing spatio-temporal systems suffer from several limitations that render them inefficient tools for spatial reasoning and decision-making (Dutta, 1988; O'Neill and Foo, 1998; Stefanakis et al., 1996). Current Spatio-Temporal systems are mostly based on Boolean (Formal) logic, a two-valued mathematical system. Because of

its limited nature, it leads to fundamental problems in the modeling and reasoning about spatio-temporal data. It has limitations in modeling and reasoning about the real world. Spatio-temporal reasoning refers in general to reasoning about problems dealing with entities occupying space over time such as cars, animals, people, oil spills, and wild fires. Spatio-temporal reasoning could be presented in three domains: qualitative, quantitative, and visual (Peuquet, 1999).

Qualitative reasoning methodologies are important, as most human reasoning is approximate in nature. For example, humans can reason in approximate terms easily to decide which path to take to reach their destination and what to do in the case of an emergency or they can predict how long it may take to travel between two locations and how a wild fire may spread. For several reasons, experts in most engineering fields routinely make inferences with much less information than detailed quantitative analysis would require. First, precise quantitative data might not be available or might be too costly to obtain. For example, at an early device-design stage, precise numerical values of the design parameters tend to be unavailable. Second, only qualitative predictions might be needed. Finally, even when engineers plan to perform detailed quantitative analysis to obtain precise results, qualitative reasoning is the crucial initial step that lets them quickly identify potential problems that warrant more detailed analysis. Qualitative-reasoning approaches offer several advantages over conventional numerical approaches including:

- Coping with incomplete data: There are situations where insufficient quantitative data is available to perform reasoning. Qualitative modeling lets us build a reasoning model and perform prediction even with incomplete knowledge.

- Imprecise but correct prediction: With qualitative methods, reasoning can proceed even when a precise numerical model is unavailable. Although, numerical methods will produce precise predictions, it is often more desirable to achieve accurate but less precise predictions.
- Easy and understandable interpretation: Numerical approaches produce numerical outputs that may be difficult to understand and interpret. However, qualitative approaches produce outputs that are easy to understand and interpret.

Qualitative reasoning can be important especially to reason about moving objects in uncertain, unknown or dynamic environments (Dutta, 1990). Qualitative reasoning attracted interest from scientists to address issues related to spatial reasoning. Forbus (Forbus, 1980) addressed issues of qualitative reasoning about space and motion. Most research on spatial reasoning has assumed well defined and crisp spatial information represented in spatial models as skeletons, generalized cones, convex polygons, Voronoi diagrams and configuration space (Dutta, 1988). In addition, visual reasoning methods that employ the power of the human visual system to detect patterns have been proposed (Dorling, 1992; Kraak and MacEachren, 1994; Monmonier, 1990).

2.3 Modeling Uncertainty

In reality, most real world events are imprecise and uncertain. However, they are represented usually with precise and crisp models, which are simplifications of the real world. The difference between reality and models is expressed by uncertainty.

There are two basic types of uncertainty that may be present in real-world situations (Kosanovic, 1995):

- Stochastic uncertainty

  Due to a lack of information the future state of the system may not be known completely. This type of uncertainty has stochastic character. It has been handled by probability theory and statistics (Papoulis, 1984; Parzen, 1962).

- Fuzziness

  Vagueness concerning the description of the semantic meaning of the events, phenomena or statements themselves (Kosko, 1993; Zimmermann, 1991).

The outcome of a stochastic event is either true *or* false with some associated probability. However, in the situation where an event itself is not well defined, the outcome may be given by a quantity other than true (one) or false (zero). That is, the outcome in the presence of fuzziness may be quantified by a degree of belief. The events are modeled as fuzzy sets because the characteristic function of such sets may take the values other than zero or one. Hence, we may talk about the probability of a fuzzy event, i.e. the likelihood that something vaguely defined would happen. Other types of uncertainty are discussed in (Klir and Folger, 1988).

Geometrical and physical models in Geodesy and GIS are more or less adequate approximations of reality. In many geographical applications there is a need to model moving objects not strictly by absolute positions but rather through vague (concepts) positions. Spatial database systems and geographic information systems are currently not able to deal with this kind of data. It is a challenge for data analysis in geographic information systems to combine the different approaches of uncertainty assessment. Commonalities and differences between the statistical and non-statistical approaches need to be understood.

There have been many efforts to handle spatial and temporal uncertainty in the past (Dyreson and Snodgrass, 1993; Shibasaki, 1994). Previous work has highlighted that standard logical approaches (i.e., Boolean logic, and random sets), classical adjustment methods (i.e., least squares adjustment), and statistics (i.e., Bayesian statistics, robust statistics, time series, Dempster-Shafer evidence theory (Lorup, 1999), possibility theory, and probability theory) are well-known mathematical methods for the analysis of uncertain data, but they are not always appropriate for modeling and reasoning about real world phenomena, which are inherently imprecise, vague, incomplete, and fuzzy in nature. Many real world phenomena including moving objects may not be represented using conventional modeling approaches due to the lack of precise knowledge about the phenomena, the strongly nonlinear behavior, the high degree of uncertainty, or the time varying patterns. There can also be situations, which encourage use of other techniques, such as lack of numeric data or having linguistic data along with the numeric data. There exist other theories that are more suitable for a number of problems. Fuzzy sets and neural network techniques are among these various techniques (Klir, 1991). Despite the fact that there is much work done on modeling spatio-temporal concepts with Boolean logic, not much has been done regarding modeling spatio-temporal concepts with Fuzzy logic (Dutta, 1990; Stefanakis, 2001; Worboys, 1996).

Uncertainty can be modeled by using Probability theory when the distributional knowledge is available which is not the case in most moving object applications (Demirli et al., 1999). The randomness assumed by probability theory describes only a restricted class of uncertainty in a system, while the majority of complex systems and real-life problems are non-random in nature. Fuzzy set theory has found its place among other

theories including Probability theory (Babuska, 1996; Hoogendoorn et al., 1998) as a new tool for representing uncertainty. Fuzzy set theory supports a large number of applications and has become one of the methods for dealing with complexity, uncertainty and imprecision in various systems. Fuzzy sets arise from an extension of the classical (Boolean) sets for representing concepts that exhibit a gradual transition from membership to non-membership. Mathematically, a set is a collection of elements that share a common property. However, there are a large number of concepts in which an element can have partial membership in a set. Fuzzy sets may be represented by a mathematical formulation known as the membership function. This function gives a degree or grade of membership within a fuzzy set. We can point out the distinction between fuzzy systems and probability as follows:

- Fuzziness is different from probability; it is the perceived uncertainty, which may be caused by randomness in the behavior of the subject.
- Fuzzy values are commonly misunderstood to be probabilities, or fuzzy logic is interpreted as some new way of handling probabilities (Bezdek, 1993). But this is not the case. A minimum requirement of probabilities is "additivity", that is that they must sum to one, or the integral of their density curves must be one. But this does not hold in general with membership grades (Klir, 1989).
- Probability statements are about the likelihood of outcomes: an event either occurs or does not. But with fuzziness, one cannot say whether an event occurred or not (Kosko, 1990). Both operate over the same numeric range, and at first glance both have similar values: 0.0 representing "false" (or non-membership), and 1.0 representing "true" (or membership).

- Probability theory assigns the membership grade of an entity in a set by a statistically defined probability function. It deals with the expectation of a future event, based on the available data. On the other hand, Fuzzy set theory describes the admission of the possibility using membership functions that an individual is a member of a set or that a given statement is true (Schneider, 1999).

  Consider the following statements:

  - The probabilistic approach:

    "There is an 90% chance that M. Jordan is tall."

  - The fuzzy approach corresponds to:

    "M. Jordan's degree of membership within the set of tall people is 0.90."

- The semantic difference is significant: the probabilistic approach supposes that M. Jordan is or is not tall; it is just that we only have a 90% chance of knowing which set he is in. By contrast, fuzzy approach supposes that he is "more or less" tall, or some other term corresponding to the value of 0.90.

- In Fuzzy set theory, the possibility that an individual belongs to a set depends on subjective factors such as expert knowledge whereas in the probability theory, probability can be computed formally or determined empirically.

- In addition, Fuzzy set theory enables vague statements about one concrete object whereas Probability theory makes statements about a collection of objects from which one is selected.

2.4 Fundamentals of the Fuzzy Set Approach

In 1965 Lotfi A. Zadeh (1965) published the first paper "Fuzzy Sets" as a novel way of characterizing non-probabilistic uncertainties by formally defining multi-valued

or fuzzy, set theory. He extended traditional set theory by changing the two-valued indicator function to a multi-valued membership function. Fuzzy set theory (or Fuzzy logic) starts with and builds on a set of user-supplied human language rules. The fuzzy systems convert these rules to mathematical equivalents. This simplifies the job of the system designer and the computer, and results in much more accurate representations of the way systems behave in the real world. The consequences of the theory, however, have not been limited to set theory only. Almost immediately, the connection between fuzzy set theory and a form of logic was recognized, leading to the introduction of fuzzy logic: a logic based on fuzzy set theory. This relation is similar to the relation between the conventional set theory and binary logic. Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary (Klir and Folger, 1988). A fuzzy set admits the possibility of partial membership such as Friday is sort of a weekend day and the weather is rather hot. A classical set might be expressed as

$$\mu_{\mathrm{A}}(\mathrm{x}) = \begin{Bmatrix} 1, & \text{if and only if x is member of A} \\ 0, & \text{if and only if x is not member of A} \end{Bmatrix} \tag{2-1}$$

A fuzzy set is an extension of this classical set. If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs:

$$A = \{x,\ \mu_A(x) \big| \, x \in X\} \tag{2-2}$$

where $\mu_A(x)$ is called the membership function (MF) of x in A.

Fuzzy logic models, called fuzzy inference systems (FISs), consist of a number of conditional "if-then" rules. For the designer who understands the system, these rules are easy to write, and as many rules as necessary can be supplied to describe the system

adequately. Not only do the rule-based approach and flexible membership function scheme make fuzzy systems straightforward to create, but they also simplify the design of systems and ensure that one can easily update and maintain the system over time. Gradual transitions (i.e., from "belongs to a set" to "does not belong to a set") characterized by membership functions give fuzzy sets flexibility in modeling commonly used linguistic expressions, such as "the travel time is high."

Since the mid-1970s, fuzzy logic has become integrated within various fields and methodologies such as fuzzy graphs, calculus of fuzzy if-then rules, fuzzy interpolation, fuzzy topology, fuzzy inference system, fuzzy modeling, and fuzzy reasoning. The earliest applications, and perhaps still the most prevalent today, were led by the research of Mamdani (1974). Multi-disciplinary applications of fuzzy logic include automatic control, electronics, pattern recognition, approximate reasoning, robotics, time-series prediction, information retrieval, database management and querying, data classification, natural language and image understanding, decision-making and machine learning (Zimmermann, 1991).

Fuzzy set theory provides a formal system to make inferences about vague rules describing the relation between imprecise, qualitative linguistic expressions of the inputs and outputs of a system (Klir and Folger, 1988). The control rules usually correspond to the knowledge of an expert and provide an easily comprehended pattern of knowledge representation. The major advantage of this approach is being able to introduce and use rules from experience, heuristics, intuition, and in addition, a model of the process is not required.

2.4.1 Fuzzy Membership Functions

Designing membership functions is a key issue in fuzzy sets (Zadeh 1965). They should be suitable for the problem at hand and easy to calculate. The outcomes of fuzzy systems may yield different results by changing the parameters of the membership functions. The selection of appropriate membership functions is an important issue. A membership function (MF) is a curve that defines how each point in the input space is mapped to a membership value. The only condition a membership function must really satisfy is that it must vary between 0 and 1. Membership functions are built from several basic functions: piecewise linear function, Gaussian distribution function, sigmoid curve, and quadratic and cubic polynomial curves (McNeill and Freiberger, 1993). Samples of fuzzy membership functions (Jang and Sun, 1995) can be seen in Figure 2.3.

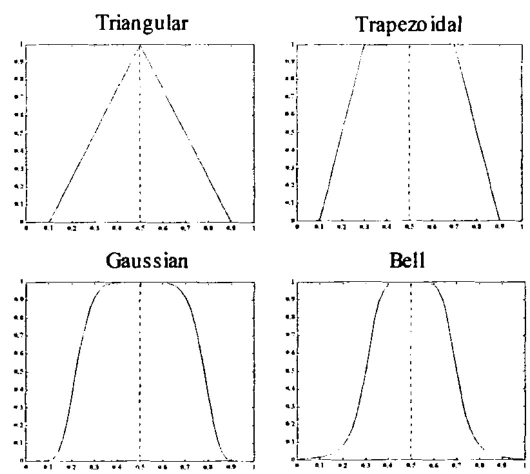


Figure 2.3: A sample set of fuzzy membership functions.

Conclusions about a certain phenomenon characterized by fuzziness are determined largely by the shape of its membership function. By using membership functions, membership grade or truth-value of a member in a particular fuzzy set is determined. The simplest membership functions are formed using straight lines. Of these,

the simplest is the triangular membership function. The trapezoidal membership function has a flat top and really is just a truncated triangle. These straight-line membership functions have the advantage of simplicity.

2.4.2 Fuzzy Inference Systems

Fuzzy inference systems (FISs) (Jang and Sun, 1995; Wang, 1994) are popular computing frameworks based on the concepts of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. It is the process of deriving conclusions from a given set of fuzzy rules acting on fuzzified data. Basically, a FIS is composed of four functional blocks as shown in Figure 2.4.

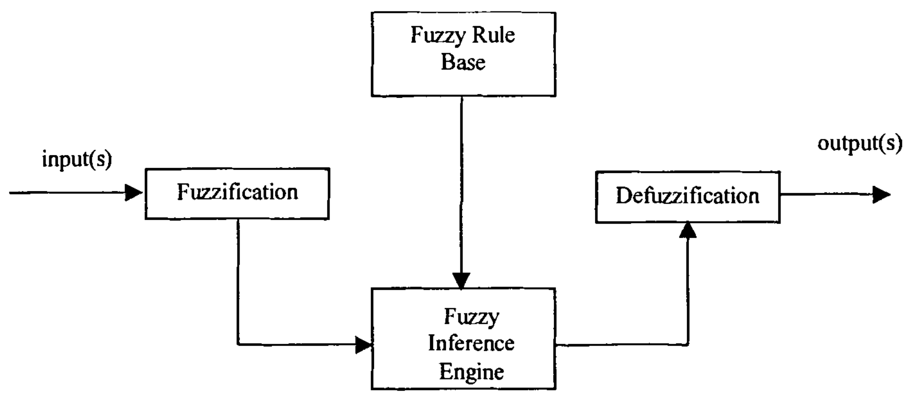


Figure 2.4: Basic fuzzy inference system.

Fuzzification maps crisp inputs into fuzzy sets, which are subsequently used as inputs to the inference engine. A fuzzy set U is characterized by a membership function (MF) μ: U→ {0,1}. Membership functions are labeled by linguistic terms such as "small" or "large" (Mendel and Mouzouris, 1997). Several classes of parameterized functions widely used to define membership functions such as Gaussian, Generalized bell, and Trapezoidal functions are given in equations (2.3), (2.4), and (2.5) respectively

$$gaussian(x;a,b,c) = \exp\left(-\left(\frac{x-a}{c}\right)^{2b}\right) \tag{2-3}$$

$$bell(x;a,b,c) = \frac{1}{1+\left|\frac{x-a}{c}\right|^{2b}} \tag{2-4}$$

$$Trapezoid(x;a,b,c) = \begin{cases} 0 & , \quad x \geq c+\frac{b}{2}+\frac{1}{a} \quad or \ x \leq c-\frac{b}{2}-\frac{1}{a} \\ 1 & , \quad x < c+\frac{b}{2} \quad or \ x > c-\frac{b}{2} \\ a\left(c+\frac{b}{2}+\frac{1}{a}-x\right) & , \quad x > c \\ a\left(x-c+\frac{b}{2}+\frac{1}{a}\right) & , \quad x \leq c \end{cases} \tag{2-5}$$

where x is an input variable, and a, b, and c are membership function parameters.

A Fuzzy rule base is a set of fuzzy rules in the form of if-then clauses. For a multi input single output case, the i^{th} rule can be expressed by

$$R^i : if \ x \ is \ A^i \ and \ y \ is \ B^i \ then \ z \ is \ C^i \tag{2-6}$$

where x and y are the input variables, z is the output variable, and A^i and B^i are the labels of membership functions associated to the input variables and C^i is the label of the membership function associated with the output variable, z, in the rule i.

Human experts are usually able to provide certain linguistic information about real world situations. However, they are usually not able to give their knowledge, experience, and intuition in terms of linguistic rules alone. In addition, certain numerical information can also be obtained based on measurements, observation, or statistical analysis of a particular phenomenon. Therefore, it is of interest to consider both numerical and linguistic information in the design process of fuzzy rules (Wang and Mendel, 1992).

A Fuzzy inference engine is a decision-making logic, which performs the inference operations on the rules and a given condition to derive a reasonable output or conclusion. In a fuzzy inference system, basically there are three types of input space partitioning: grid, tree, and scattering partitioning (MathWorks, 1995). Three types of FISs (Jang and Sun, 1995): Mamdani fuzzy model, Sugeno fuzzy model, and Tsukamoto fuzzy model, have been widely employed in various applications. The differences between these three FISs lie in the consequents of their fuzzy rules, and thus their aggregation and defuzzification procedures differ accordingly.

The Mamdani fuzzy model (Mamdani and Assilian, 1975) was proposed as a first attempt to control a steam engine and boiler combination using a set of linguistic control rules obtained from experienced human operators. Figure 2.5 shows how a two-rule fuzzy inference system of the Mamdani type works to calculate the overall output z when subjected to two crisp inputs x and y.

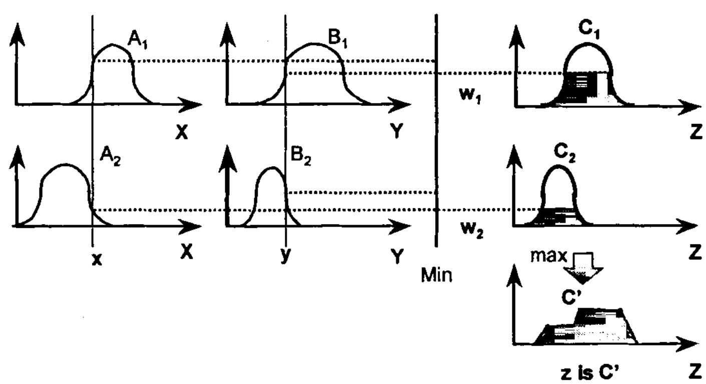


Figure 2.5: Mamdani type fuzzy inference system.

The Sugeno fuzzy model was proposed in an effort to develop a systematic approach to generating fuzzy rules from a given input-output data set. Figure 2.6 shows how a two-rule fuzzy inference system of the Sugeno type works to calculate the overall output z when subjected to two crisp inputs x and y.

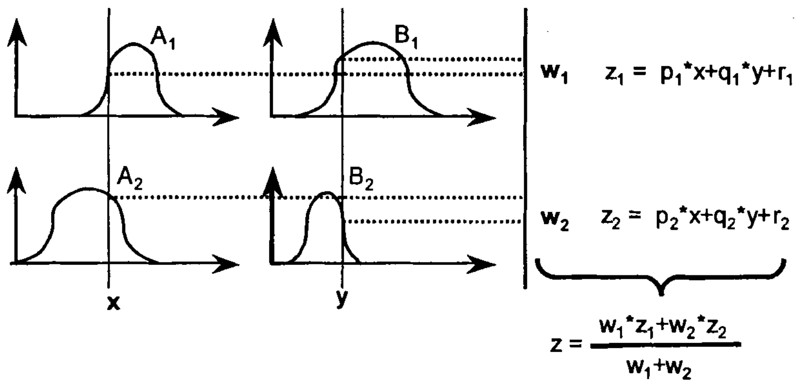


Figure 2.6: Sugeno type fuzzy inference system.

A typical fuzzy rule in a Sugeno fuzzy model has the form

$$R^i : if\ x\ is\ A^i\ and\ y\ is\ B^i\ then\ z = f^i(x,y) \tag{2-7}$$

where A^i and B^i are fuzzy sets and $z = f^i(x; y)$ is a crisp function. Usually f (x; y) is a polynomial of the input variables x and y and the fuzzy inference system that uses a first-order polynomial f (x; y) is called a first-order Sugeno fuzzy model (Sugeno and Kang, 1988; Takagi and Sugeno, 1985).

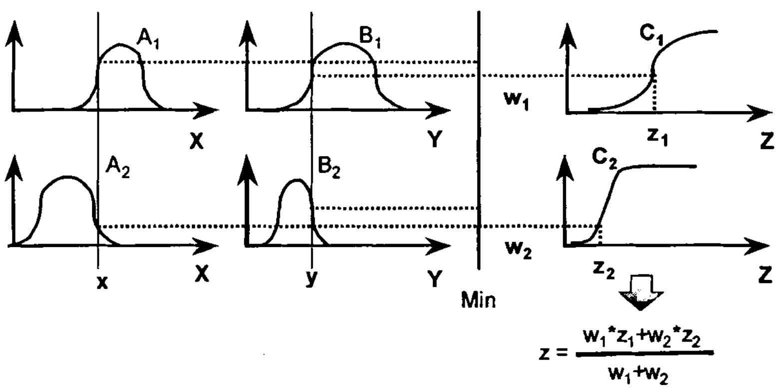


Figure 2.7: Tsukomato type fuzzy inference system.

In the Tsukamoto fuzzy models (Tsukamoto, 1979) the result of each fuzzy if-then rule is represented by a fuzzy set with a monotonical MF. The overall output is taken as the weighted average of each rule's output. The whole reasoning procedure for a two-

input two-rule system can be seen in Figure 2.7. Since each rule infers a crisp output, the Tsukamoto fuzzy model aggregates each rule's output by the method of weighted average and thus also avoids the time-consuming process of defuzzification.

Defuzzification transforms the fuzzy results of the inference into a crisp output. The most popular defuzzification method is the centroid of area as given in equation (2.8).

$$output = \frac{\int_Z z\mu_{C'}(z)dz}{\int_Z \mu_{C'}(z)dz} \tag{2-8}$$

where $\mu_C(z)$ is the aggregated output MF. Other defuzzification strategies arise for specific applications, which include bisector of area, mean of maximum, largest of maximum, and smallest of maximum, and so on. These defuzzification strategies (Jang and Sun, 1995) are shown in Figure 2.8.

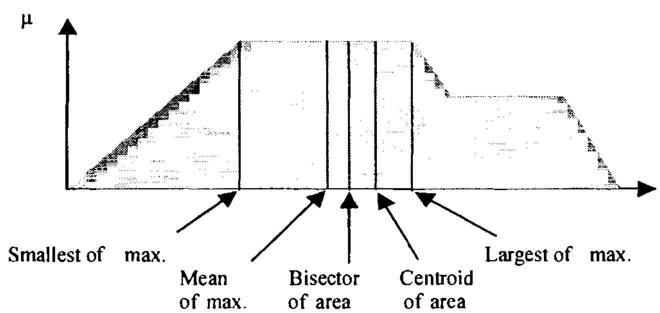


Figure 2.8: Defuzzification strategies (Jang and Sun, 1995).

The essential part of a typical fuzzy system is formed by a knowledge base in which the process of the fuzzy system is explained as a set of fuzzy if-then rules. An inference mechanism compares the inputs of the system against the knowledge stored in the knowledge base and generates a system's output by using the given inputs and the available knowledge in the knowledge base. Conventional fuzzy systems are static; rules

are acquired off-line and the system components do not change once operation begins. Adaptive fuzzy systems are capable of modifying their behavior to follow changes in the operating environment. This adaptive capability is crucial in complex problem domains such as in many military applications, where it is desirable to have the system react to newly acquired or dynamically changing knowledge. In this thesis, the implementations of both conventional and adaptive neuro-fuzzy systems are demonstrated.

2.5 Neuro-Fuzzy Modeling

The term neuro-fuzzy modeling refers to the way of applying various learning rules developed in the artificial neural network (ANN) literature to fuzzy systems. Compared to black-box techniques like neural networks where the internal structure of the network (the functioning of the ANN) is hardly transparent to the user, fuzzy systems are to a certain degree transparent to interpretation and analysis. In the 1990s, several transportation applications used Artificial Neural Networks (ANN) (Dougherty and Kirby, 1993). In this work, driver behaviors under changing conditions were analyzed. ANN was used in the prediction of rates created by traffic flow according to the possible traffic compositions (Kikuchi et al., 1993; Ritchie and Cheu, 1993).

Although the fuzzy inference system has a structured knowledge representation in the form of fuzzy if-then rules, it lacks the capabilities of learning and has no memory. In the classical development of fuzzy systems, fuzzy rules have been obtained by knowledge acquisition from experts. Recently, algorithms have been developed to learn fuzzy rules from numerical training data. Among them, the back-propagation learning rule, which is actually a universal learning paradigm for any smooth parameterized models including fuzzy inference systems, was introduced. The ability to generate fuzzy

rules from training samples has distinct advantages in many applications. That is why hybrid systems particularly neuro-fuzzy systems are becoming popular. As a result, a fuzzy inference system can now not only take linguistic information (linguistic rules) from human experts, but also numerical data (input/output pairs) to achieve better performance. This gives fuzzy inference systems an edge over neural networks, which cannot take linguistic information directly (Kosko, 1992).

Fuzzy sets, neural networks, and neuro-fuzzy methods are among the methods used to model uncertain and imprecise information (Altman, 1994; Dragicevic and Marceau, 1999; Klir and Folger, 1988; Schneider, 1999; Studer and Masulli, 1996) by many fields including modeling moving objects. In this research, fuzzy and neuro-fuzzy techniques are adopted to develop models of moving objects and to capture the imprecision, uncertainty, and vagueness related to their movements.

2.6 Adaptive Neuro-Fuzzy Inference System

An Adaptive-Network-based Fuzzy Inference System (ANFIS), is a fuzzy inference system implemented in the framework of adaptive networks (Jang, 1993). An adaptive network is a superset of all kinds of feed-forward neural networks with supervised learning capability. ANFIS serves as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input-output pairs. Modeling and control techniques of ANFIS are explained in (Jang and Sun, 1995) and a number of various applications are demonstrated in (Jang et al., 1996). The remaining paragraphs explain the ANFIS architecture and its learning algorithm for the Sugeno fuzzy models (Jang, 1993; Studer and Masulli, 1996).

We assume that the fuzzy system under consideration has two inputs x and y and one output z. Consider a first-order Sugeno type fuzzy system (Sugeno and Kang, 1988; Takagi and Sugeno, 1985) having a typical rule base as follows:

$$Rule\,1\text{:If } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = p_1x + q_1y + r_1 \tag{2-9}$$

$$Rule\,2\text{:If } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = p_2x + q_2y + r_2 \tag{2-10}$$

Figure 2.9 illustrates the reasoning mechanism for this Sugeno model (Takagi and Sugeno, 1983) and the equivalent ANFIS architecture is shown in Figure 2.10.

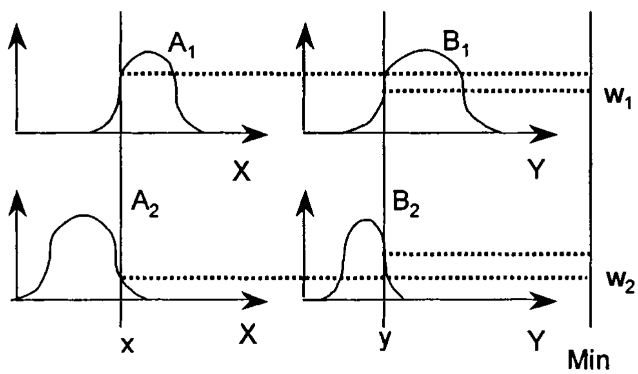


Figure 2.9: A two-input first-order Sugeno fuzzy model with two rules.

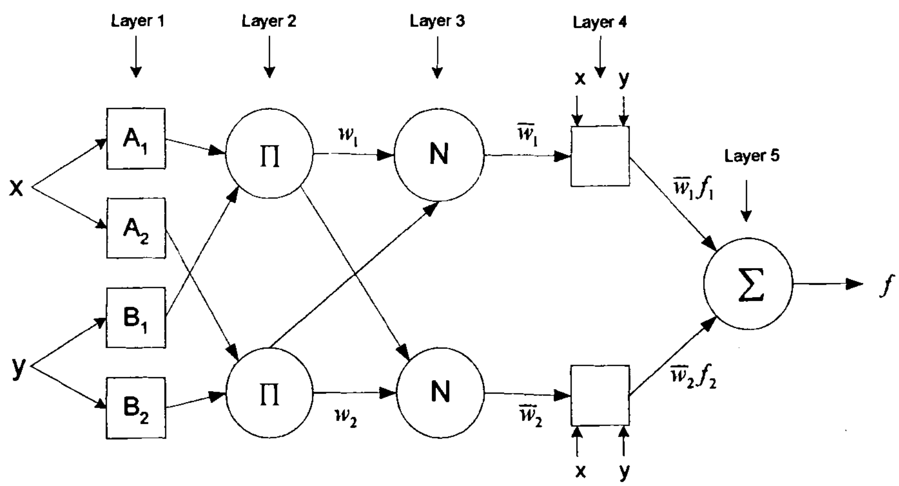


Figure 2.10: The equivalent ANFIS structure.

Every node i in Layer 1 is an adaptive node with a membership function $\mu_{A_i}(x)$ of fuzzy set A_i and $\mu_{B_i}(y)$ of fuzzy set B_i $(i = 1,2)$. Here, x is an input value and A_i is the linguistic label (close, far, etc.) associated with the membership functions. Parameters used in this layer are referred to as 'premise parameters'.

Every node in Layer 2 is a fixed node labeled Π which multiples the incoming signals and outputs a product.

Evaluating the rule premises results in

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1,2. \tag{2-11}$$

Evaluating the implication and the rule consequences gives

$$f(x,y) = \frac{w_1(x,y) f_1(x,y) + w_2(x,y) f_2(x,y)}{w_1(x,y) + w_2(x,y)} \tag{2-12}$$

Or leaving the arguments out

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{2-13}$$

Every node in Layer 3 is a fixed node labeled N. The i-th node calculates the ratio of the i-th rule's firing strength to the sum of all rules' firing strengths:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{2-14}$$

Every node i in Layer 4 is an adaptive node with a node function

$$\overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{2-15}$$

where $\overline{w}_i$ is the output of layer 3, and $(p_i x + q_i y + r_i)$ is the parameter set. Parameters used in this layer are referred to as 'consequent parameters'.

The single node in Layer 5 is a fixed node labeled $\sum$ that computes the overall output as the summation of all incoming signals and is written as

$$f = \sum_i \overline{w}_i f_i = \overline{w}_1 f_1 + \overline{w}_2 f_2 \qquad (2\text{-}16)$$

In the context of this thesis, this approach is used to interpolate the movement data to obtain movement signatures.

2.7 Data Mining

Data Mining is the process of identifying new patterns and insights in data. As the volume of data collected and stored in databases grows, especially in moving object applications, there is an increasing need to provide data summarization, identify important patterns, and reason upon the findings.

There are currently few geographical analysis methods able to explore large databases for detecting and summarizing movement patterns. As a result many important datasets are not being analyzed to the fullest extent. For example, data about movements of animals, city busses, and criminals are collected and analyzed, if indeed at all, using inadequate methods. Here, the essential task of data mining, which employs forms of cluster analysis, is to find clusters and patterns in space and/or time in movement data. The purpose of clustering, which is also called unsupervised learning, is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior (Krishnapuram and Keller, 1993). Clustering of numerical data forms the basis of many classification and system modeling algorithms. There are several clustering models and algorithms that are developed based on crisp (Duda and Hart, 1973), fuzzy (Bezdek, 1981), probabilistic (Titterington et al., 1985), and possibilistic methods (Krishnapuram and Keller, 1993).

Assigning each data point to exactly one cluster often causes problems, because in real world applications a crisp separation of clusters is rarely possible due to overlapping classes. Also there are usually exceptions, which cannot be suitably assigned to any one cluster. Fuzzy clustering methods that specify a membership degree between 0 and 1 for the assignment of each data sample to multiple clusters instead of crisp assignments of the data to a single cluster are better suited for several applications. Most fuzzy cluster analysis methods optimize a subjective function that evaluates a given fuzzy assignment of data to clusters. By suitable selection of parameters of the subjective function it is possible to search for clusters of different forms. From the result of a fuzzy cluster analysis, a set of fuzzy membership functions can be obtained to describe the underlying data. These fuzzy membership functions can be used to build fuzzy movement signatures of objects. Classification of movement observations into signatures may also be handled by using clustering methods. We can cluster different types of movement observations in regard to the distances, directions, speeds, and temporal behaviors they exhibit. In this thesis, an approach is introduced for the analysis of movement data to produce rules to as *where* to look for patterns, *when* to look, and *what* to look for. In order to carry out our proposed approach different clustering methods including the iterative self-organizing data analysis technique (Isodata) and fuzzy c-means are used.

2.7.1 The Iterative Self-Organizing Data Analysis Technique

The iterative self-organizing data analysis technique (Isodata) is a widely used technique in unsupervised data clustering (Bezdek, 1980; Dunn, 1973; Takahashi et al., 1995). The Isodata clustering method (Tou and Gonzalez, 1974) iteratively classifies data, redefines the criteria for each class, and classifies again, so that the Euclidian

distance patterns in the data gradually emerge. Isodata provides a means to automatically determine the optimal number of clusters by splitting and merging clusters. The way in which it locates clusters with minimum user input is referred to as self-organizing. In order to carry out Isodata clustering, one needs to determine:

- The maximum number of clusters, *N*, to be considered. This number is the maximum number of classes to be formed
- The convergence threshold *T*, which is the maximum percentage of data whose cluster assignments are unchanged between iterations. This prevents the Isodata algorithm from running indefinitely.
- The maximum number of iterations *M* to be carried out.

The means of *N* clusters can be arbitrarily identified on the first iteration of the Isodata algorithm. As a result of each iteration, a new mean for each cluster is computed based on the actual Euclidian locations of the data in the cluster. Then, these new means are used for defining clusters in the next iteration. The process continues until there is little change between iterations (Swain, 1973).

Isodata method is composed of the following procedures:

- All members are relocated into the closest clusters by computing the distance between the member and the cluster center.
- The center of all clusters is recomputed and the above procedure is repeated until convergence. It is possible for the percentage of unchanged data to never converge or reach *T*. Therefore, it may be beneficial to monitor the percentage, or specify a reasonable maximum number of iterations, *M*.

- If the number of clusters is within a specified number, and the distances between the clusters meets a prescribed threshold, the clustering is considered complete.

Please refer to (Schalkoff, 1992; Therrien, 1989) for more information about Isodata clustering method.

2.7.2 Fuzzy C-Means Clustering

Fuzzy c-means (FCM) (Xie and Beni, 1991) is a data clustering method wherein each data point belongs to a cluster to some degree that is specified by a membership grade. FCM technique was originally introduced by Bezdek (1981) as an improvement on earlier clustering methods. It provides a method for grouping data points that populate some multidimensional space into a specific number of different clusters. The cluster information can be used to generate a Sugeno-type fuzzy inference system that best models the data behavior using a minimum number of rules. The rules partition themselves according to the fuzzy qualities associated with each of the data clusters.

In moving objects applications often there are no sharp boundaries between clusters so that fuzzy clustering is better suited for the movement data. Membership degrees between zero and one are used in fuzzy clustering instead of crisp assignments of the data to clusters. Fuzzy clustering can be applied as an unsupervised learning strategy in order to group data. But fuzzy clustering is also very useful for constructing fuzzy if-then rules from data. The structure of the rules depends on the considered application. Identifying the structure of a fuzzy system requires designing the appropriate input and output membership functions and enough rules, which is achieved by rule generation and input selection steps.

In this thesis, rule generation is carried out using the approach of Emami et al. (1996) based on clustering of input-output data. The fuzzy partition of the input space is specified by generating the projection of the output clustered space on each input variable separately. Using this method, the rule generation step could be separated from the input selection step. The idea of fuzzy clustering is to divide the output data into fuzzy partitions that overlap each other. Therefore, the containment of each data within a cluster is defined by a membership grade, which takes values in the interval of [0, 1]. The clustering of the unlabeled data $X = \{x_1, x_2, ..., x_N\} \subset \Re^h$ is the assignment of labels to the vectors in X and to the objects generating X. Here, N is the number of data vectors and h is the dimension of each data vector. The problem of fuzzy clustering is to find the optimum membership matrix U. The most widely used objective function for fuzzy clustering in X is the weighted within-groups sum of squared errors objective function J_m, which is used to define the following constrained optimization problem (Bezdek, 1981):

$$\min_{(u,v)} \left\{ J_m(U,V;X) = \sum_{k=1}^{N} \sum_{i=1}^{c} (u_{ik})^m \left\| x_k - v_i \right\|_D^2 \right\} \tag{2-17}$$

where

$$U \in M_{fcn} = \left\{ U \in \Re^{cN} \middle| \begin{array}{l} o \le u_{ik} \le 1 \;\; \forall i,k \;\; \& \;\; \forall k,\; u_{ik} > 0 \;\; \exists i \\ o < \sum_{k=1}^{N} u_{ik} < n \;\; \forall i \;\; \& \;\; \sum_{i=1}^{c} u_{ik} = 1 \;\; \forall k \end{array} \right\} \tag{2-18}$$

Here, $V = \{v_1, v_2, ..., v_c\}$ is a vector of (unknown) cluster centers, and $\|x\|_A = \sqrt{x^T A x}$ is any inner product norm. A is a $h \times h$ positive definite matrix which specifies the shape of the clusters. The common selection for the matrix A is the identity matrix, leading to the definition of Euclidean distance, and consequently to clusters.

Fuzzy partitions are carried out using the fuzzy c-means algorithm through an iterative optimization of J_m (Pal and Bezdek, 1995). The procedure can be summarized in the equation (2.21) (Pal and Bezdek, 1995).

$$u_{ik,t} = \left[\sum_{j=1}^{c} \left(\frac{\|x_k - v_{i,t-1}\|_D}{\|x_k - v_{j,t-1}\|_D} \right)^{\frac{2}{m-1}} \right]^{-1} \tag{2-19}$$

$$v_{i,t} = \frac{\sum_{k=1}^{N} (u_{ik,t})^m x_k}{\sum_{k=1}^{N} (u_{ik,t})^m} \tag{2-20}$$

(2-21)

1. *Store unlabeled object data* $X = \{x_1, x_2, \ldots, x_N\} \subset \Re^h$
2. *Pick* *number of clusters (c),*

   weighting exponent (m),

   iteration limit (T), termination criterion $(\varepsilon > 0)$,

   Norm for J_m $(\|x_k - v_i\|_A)$, *and Norm for* $E_t = \|V_t - V_{t-1}\|$.
3. *Guess initial position of cluster centers:* $V_0 = \{v_{1,0}, v_{2,0}, \ldots, v_{c,0}\} \subset \Re^{ch}$.
4. *Iterate* *For* $t = 1$ *to* T;

   Calculate $u_{ik,t}$

   Calculate $v_{i,t}$

   If $E_t \le \varepsilon$, *Then stop, and put* $(U_f, V_f) = (U_t, V_t)$

   Next t
5. *Use prototypes* V_f *and/or fuzzy Labels* U_f

Cluster validity index is an important issue in the fuzzy clustering. In this study, the Emami index (Emami et al., 1996), which is an appropriate generalization of scattering criteria (Duda and Hart, 1973) for the assignment of number of clusters, is performed.

Another parameter whose value should be decided in fuzzy clustering is the weighting exponent m, shown in the equations (2.19) and (2.20). Weighting exponent controls the extent of membership sharing between fuzzy clusters in the data set. Therefore, in the range of $(1,\infty)$, the larger m is, the "fuzzier" are the membership assignments to each data point. A guideline for the selection of m is introduced by Emami et al. (1996). In this study, the value of the weighting exponent m=2 is used in order to obtain fuzzy cluster centers.

The input selection in fuzzy system identification is to find the most dominant input variables among a finite number of input candidates. In this study, the input selection is carried out using the proposed method of Emami et al. (1996). In this method, input selection is directly related to the way input membership functions are constructed. The membership functions for each input candidate were constructed through fuzzy clustering such that, for each cluster, those points which have output membership grade close or equal to one obtain the same input membership grades.

Chapter 3

MODELING MOVING OBJECTS

We consider moving objects to be real world objects capable of voluntary or involuntary movement. For instance, cars, trains, ships, airplanes, insects, birds, animals, humans are moving objects. Moving objects may include those that are frequently at rest to those that exhibit continuous movement. Erwig et al. (1999) characterizes all geometric change as movement including changes in shape (growing or shrinking). Galton (1995) describes movement as occurring whenever the same object occupies different positions in space at different times. He describes the position of an object as the total region of space that it occupies at a time. We separate change in an object's boundary and expansion or contraction of size as a shape change and distinguish it from movement. We define movement specifically as a translation or rotation about an axis (similar to the definition used by (Moreira et al., 1999)). This distinction captures important behavioral differences between real world objects for example lakes and cars. Lakes frequently shrink and expand but are not subject to rotation or translation and hence we would say are not subject to movement (except possibly in a catastrophic event). Cars on the other hand frequently change their positions but do not change their shape. Both rigid and non-rigid objects may exhibit both types of change: movement and boundary reconfiguration and there can be reason and need to treat these as separate dimensions of change.

3.1 Model Framework for Movement Behaviors

Rarely are movements completely random and rarely are they completely unconstrained. They are organized by spatial and temporal structures and the physical properties of an object itself. To characterize the spatial aspect of a moving object, the position of the object should be captured. To characterize the spatio-temporal aspect of a moving object, which gives us its path, the orientation, direction, distance, travel time, and speed of the object should be captured. Complete knowledge of any particular movement is impossible, but movements can be detected, modeled and predicted with some degree of accuracy and reliability. A model for moving objects should be able to support several types of questions about moving objects. Some questions may deal strictly with spatial patterns, others may deal with only temporal aspects while others address combined spatial-temporal patterns. Useful spatio-temporal information on a single moving object at time t may be addressed with the following questions:

- What is the position of a moving object at time t?
- What is the orientation of a moving object at time t?
- What is the direction of the movement of a moving object at time t?
- What is the distance of a moving object at time t from certain locations?
- What is the speed of a moving object at time t?
- What is the path of a moving object during time interval I (t_{i-1}, t_i)?

In order to effectively model moving objects we need a representational framework for movement behaviors. Most previous approaches to estimating moving object positions rely on a time ordered sequence of observations. Observations refer to any measurements that capture the location of one or more real world objects at specific

times. Several approaches have indicated the need to amend recorded positions with additional information at higher levels of abstraction. Wolfson et al. (1999) add a motion plan which is a sequence of way-time points (p_i, t_i) indicating where (p_i) a moving object will be at time t_i. A motion plan is deterministic information on an individual object. This approach assumes that the system has prior information about how an object is going to move over time, which may not often be the case.

The framework proposed in this thesis for organizing information on movement behavior is illustrated in Figure 3.1. There are three components of the framework: movement profiles, observations, and movement signatures. This structure reflects various types of information likely to be available on moving objects. Profile level information is very general information known for a class of objects. Observations are captured information for individual moving objects that typically include a record of position and orientation at a particular time. Signatures, the core concept developed in this thesis, are space-time summaries of an individual object based on a collection of observations. Each of these components is described further in the next sections.

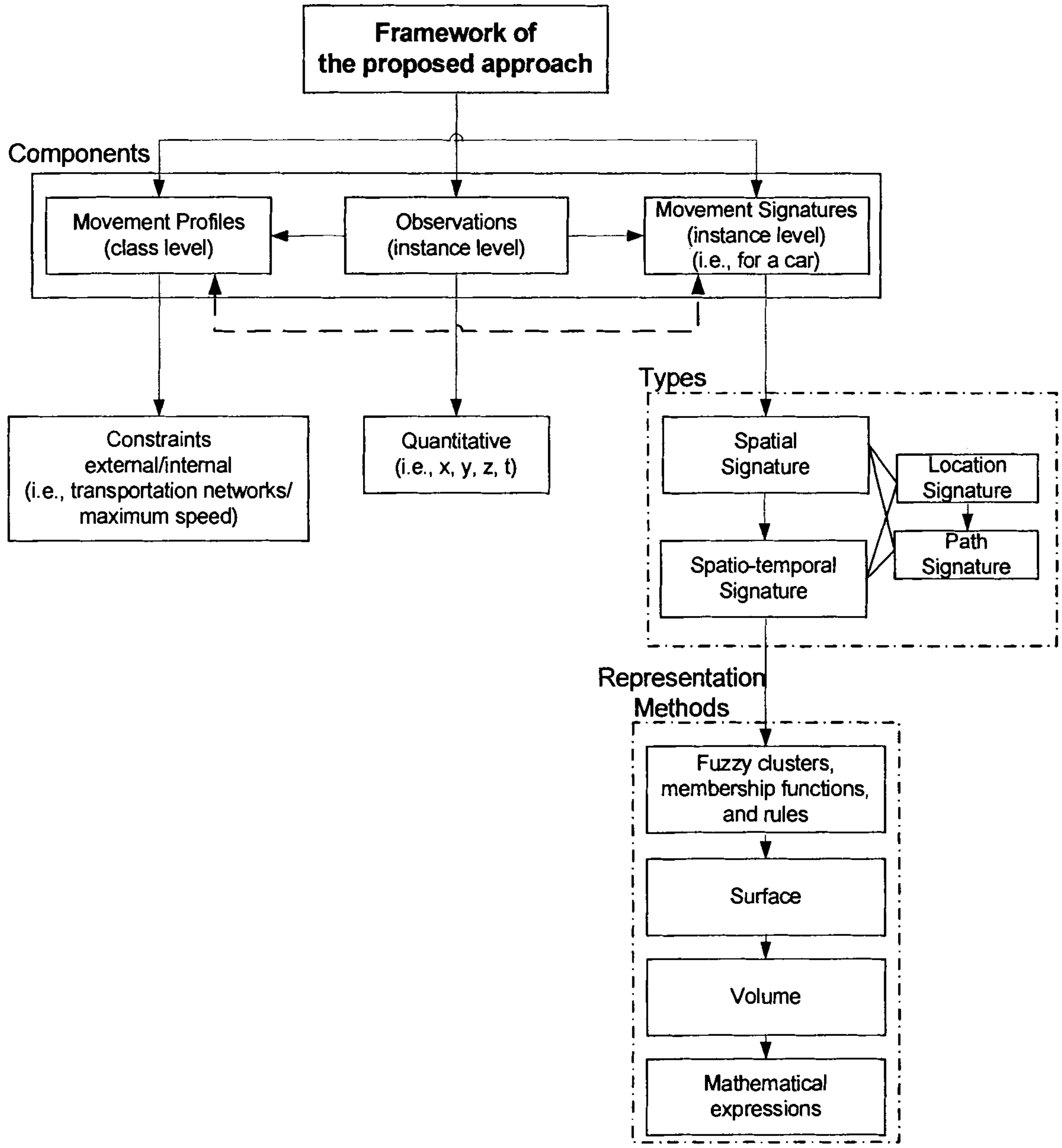


Figure 3.1: The framework of the proposed approach.

3.1.1 Movement Profiles

Profile information describes general knowledge on the movement behaviors of classes of objects such as cars, planes, boats, and various types of animals. We know that moving objects have general constraints on their movements (i.e., boats are constrained to water). We refer to the general class level behaviors and constraints as movement profiles. The range of movement behaviors belonging to a set of objects such as a car, a truck, and a bus forms the general movement behaviors of a class of object such as the class "vehicle". Most objects move within constrained environments such as roads and many classes of objects is subject to similar sets of constraints. Thus profile level information can be specified in the form of constraints applied to a class. Movements of objects are subject to various spatial and temporal constraints and movement profiles identify these constraints. We identify two types of physical constraints on movements of objects:

- Internal Constraints: These are related to the physical characteristics of a class of moving objects that define the objects' ability to move. Such constraints bound speed, agility, and ability to move in different media or along different axes.
- External Constraints: These are constraints that exist in the environment external to an object. A class of moving objects usually shares sets of external constraints including spatial and temporal constraints such as moving on the same type of media.

A movement profile for a class of objects identifies directional axis constraints on movement, medium constraints on movement, general size, shape and weight characteristics that constrain movement, as well as prototypical average or maximum

speed for a class of object. These sets of constraints can be associated with class hierarchies. As an example, classes of vehicles, classes of animals or classes of storms can be globally assigned average or maximum speeds. Subsets of classes with different behaviors can be assigned to subclasses distinguished by different directional movement constraints or different media constraints. Directional axis movement constraints describe the ability of an object to move in the X, Y or Z-axis where these are aligned with respect to the object itself as shown in Figure 3.2.

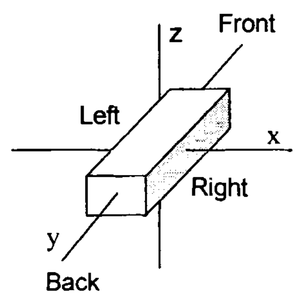


Figure 3.2: Axes used to describe the directional axis movement constraints of objects.

We assume an object has a fixed orientation: a front and back aligned with the Y-axis and a left and right aligned with the X-axis. Z is the vertical axis aligned with the gravitational field. Some objects are capable of movement along all three axes, but to different degrees. For example, humans' primary axes of movement is Y. However, they can engage in X movements by sidestepping, but are significantly constrained in Z. In addition, helicopters are capable of Y movement, Z movement, and X movement, a submarine has Z and Y movement, an elevator only Z movement, and a car just Y movement. Media constraints are external constraints referring to the surface or volumetric media on or within which an object is capable of moving. Very few objects are unconstrained with respect to media. Obvious examples of media constraints include

roads for automobiles, tracks for trains, and water for ships. Animals, people, and all terrain vehicles are examples of less media constrained moving objects.

Constraints on class level movements can take the form of either spatial or temporal constraints. An animal's spatial constraints can include inability to move up steep gradients, through thick underbrush, or over water. Its temporal constraints may be that it routinely moves only during the day or only during the night. Media may have their own constraints that a moving object may inherit. For example all classes of moving objects have a prototypical speed. Cars constrained to the road media inherit the speed limits assigned to the roads, which in turn may override their prototypical speed. Knowledge of an object's movement constraints in the form of profiles in combination with observations can improve the ability to more reliably estimate a moving object's location or path. Profiles are introduced as an essential component of the overall framework and to indicate that they place bounds on signature level movement behavior. This thesis however does not focus on movement profile development.

3.1.2 Observations

While movement profiles provide general information on how classes of objects may or may not move, observations are the important information component for determining specific positions occupied by moving objects and the associated time of occupation. Observations refer to any measurements that capture the location of one or more real world objects. We identify two types of observation: qualitative (linguistic) such as the speed of the car was slow and it was heading north-east and quantitative (numeric) such as the speed of the car was 45.73 mile/hour and it was heading 62.56 degree north-east.

Qualitative observations are usually acquired from the knowledge or perception of experts in specific applications. Human decision-making and reasoning in movement modeling uses qualitative observations and knowledge on a daily basis when reasoning about movements of objects. In many situations humans use linguistic information more easily than numerical information. We need to combine quantitative knowledge (formulas and equations, i.e., direction of moving object is 63.16^{o}) and qualitative knowledge (linguistic information, i.e., direction of moving object is Northeast) when solving real-life problems related to movements of objects. Therefore, qualitative observations are used to build the fuzzy membership functions and fuzzy rules base of the ANFIS structure developed in this thesis along with the quantitative observations.

The sources of quantitative observation include satellite images, aerial photographs, video sequences, GPS observations, or telemetry observations. Moreira et al. (1999) refer to observation-based systems as sensor systems that capture location data in an ordered sequence at regular time intervals. In comparison with GPS observations, images are less effective observation sources for identifying and tracking specific moving objects. In certain contexts, however, imagery including that from video cameras may be useful sources for obtaining moving object positions.

We assume that observations may be regularly or irregularly spaced in time from different sources. Representations of these observations are stored in a database. For each observation we assume a recorded spatial footprint that describes a 2D projection of the observation into a spatial reference frame (Beard and Smith, 1997). Such projections or footprints may take the form of points, lines, or regions. A GPS observation has a point footprint while a satellite image or the extract of an object from an image will have a

region footprint. A video clip may have a point, linear, or regional footprint. Observations additionally have time stamps that may be points or intervals.

The proposed spatio-temporal model for organizing observational data (Figure 3.3) (Beard and Agouris, 1997) includes a multimedia information store, which is the repository of information sources that may include imagery, maps, video, text documents, and scientific data sets such as meteorological observations, and a spatio-temporal gazetteer. The spatio-temporal gazetteer (Figure 3.3) is an indexing structure over the multimedia information store and is the key mechanism for converting latent information contained in the multimedia information store into explicit observations on individual objects.

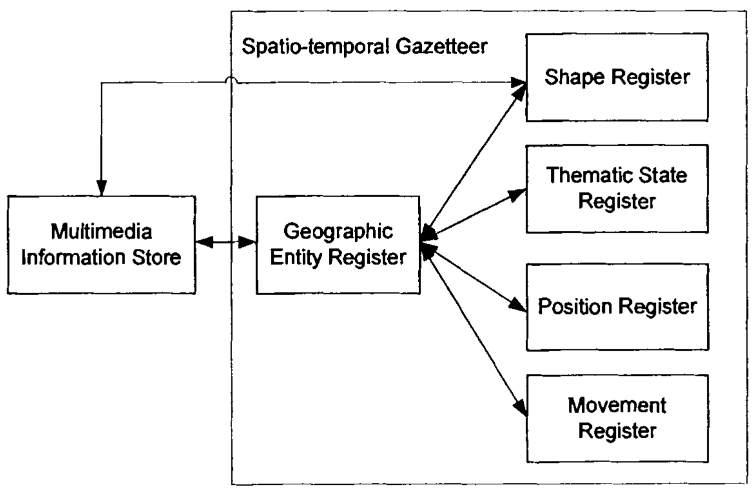


Figure 3.3: Conceptual model of integrated spatio-temporal gazetteer and multimedia information store.

The gazetteer consists of several subcomponents including:

- a geographic entity register,
- a spatial representation register,
- a thematic state register,
- a position register,
- a movement register.

The geographic object register maintains a record of identified spatio-temporal objects. When an object is identified and registered it receives a unique identifier, a register entry date, a name and a generalized spatial location or footprint. The shape register is a collection of relations between geographic objects and the boundary representations of individual objects. It tracks boundary representations of geographic objects. In a similar manner, the thematic state register tracks thematic states of geographic objects. The position register tracks positions of objects. And finally, the movement register tracks movements of objects (Beard and Agouris, 1997).

A GPS observation is typically associated with a single real world object (i.e. a ship). Satellite or other imagery, however, contains representations of multiple real world objects and their positions. Objects and their positions are extracted from images using various feature extraction methods (Agouris et al., 2000b; Mountrakis, 2000). The position register maintains the association between an observed position and an object.

object_id, observation_id, observation_time_stamp, x-y coordinates

This association is important for accuracy assessment, as the accuracy of the position is a function of characteristics of the observation and the applied feature extraction method. A similar approach has been introduced by Pfoser et al. (2000).

If an object is extracted from an image we describe its position as a point or center of the object's minimum bounding rectangle (MBR). B:position: $(x,y,z,\theta)_{Oti}$ describes B's location according to the observation O_{ti} with time stamp ti; x, y, and z are coordinates describing the MBR center, and θ is an initial azimuth for the object if a record of azimuth is pertinent. Plotted a set of position observations for an individual object on an individual day might look like those illustrated in Figure 3.4.

Movement of an object cannot be detected from a single observation (i.e., a single GPS observation) since a single observation is assumed to represent an instant of time. Detection of movement requires at least two observations with different time stamps defining a time interval. A record in the movement register contains the unique ID of a geographic object, a distance and direction vector indicating movement of the geographic entity, the IDs of the two information objects from which the vector was extracted, and the time interval computed as the difference between the two observation time stamps. Two different observations a short time interval apart can indicate a movement. We say movement has occurred if for Δt (the difference in time stamps between two observations), there is a ΔX, ΔY, ΔZ, or $\Delta\theta$ greater than zero, and a *unit movement* is defined as given in equation (3.1).

$$B : movement_{01,02} = (\Delta X, \Delta Y, \Delta Z, \Delta\theta) \tag{3-1}$$

A unit movement has the properties of duration (Δt), path (ΔX, ΔY, ΔZ, or $\Delta\theta$) and velocity (ΔX, ΔY, ΔZ)/Δt, or $\Delta\theta/\Delta t$. The unit movement vectors may be maintained in the movement register or computed as needed.

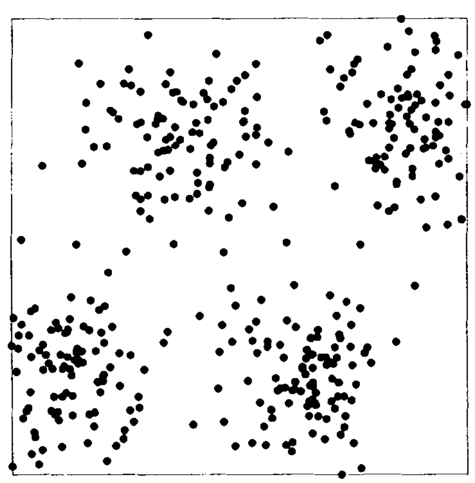


Figure 3.4: A set of position observations.

3.2 Movement Signatures: What is a Signature?

In a sense, the profiles and the observations are information at the extremes. The profiles offer general information that identifies the capabilities of an object to move, while the observations provide relatively high frequency information on the positions of individual objects at particular times. What is not addressed by either but may be of some interest for a number of applications is information on the general movement patterns of an individual object. For example we might want to ask about the general movement of a soccer mom on Monday mornings, the weekly pattern of a tugboat in Portland harbor, the patterns of bear # 105 in the spring, the annual pattern of a migrant laborer or the annual pattern of a long haul trucker. In each example, the interest is in same likely patterns for same time intervals. The implication from the examples is that every moving object in the real world exhibits a wide range of behaviors some of which repeat but not exactly over space and time. Even though movement behaviors are not exactly the same, they are also not completely different. Moving objects may move on the same or nearly similar paths and visit the same locations over time. There is a thread of continuity, similarity, and predictability that allows us to generalize from past behaviors to future behaviors.

This thesis seeks to represent the patterns of moving objects with movement signatures. Detecting a movement signature and defining its attributes is a significant piece of information in modeling and reasoning about moving objects. One can see where, when, and how strongly a movement pattern reoccurs. Describing and recognizing such movement signatures contributes to knowledge building and knowledge reuse in the modeling of moving objects. Signatures can be used to capture the temporal changes in

an object's movements (e.g., a summer versus winter pattern). They can be used for comparative analysis of dominant patterns among different individual of the same class of moving objects. And they can also help to identify significant behavioral differences between different moving objects such as movement of a city bus versus movement of an ambulance.

A movement signature is a summary of movement observations on an object over some period of time (Beard and Palancıoğlu, 2000). We define a movement signature as a significant, high-level structure present in the data. A movement signature condenses and summarizes large amounts of observations in numeric, graphic, or linguistic formats. Any movement that cannot be represented by a simple movement signature is defined as random movement.

This thesis develops a model of signatures for moving objects that is learned from observations and bounded by profile level information. Movement signatures are higher-level abstractions of observations that capture dominant patterns of a moving object over time. Assume a set of position observations belonging to an object as given in (3.2) and illustrated in Figure 3.4:

$$\Lambda = \{(x_1, y_1), (x_2, y_2), \ldots\ldots, (x_n, y_n)\} \tag{3-2}$$

This thesis defines a **position** as an x-y coordinate pair representing a point observation of a moving object. On the other hand, a set of observed positions associated with a specified fuzzy boundary is referred to as a **location** such as set of observed positions representing the "city of Orono" as shown in Figure 3.9.

Our approach analyses and summarizes observations of moving objects to allow learning of movement signatures such that future behaviors can be predicted. The objective of the movement signature development is to arrive at these dominant movement patterns of an individual for different spatial (i.e., city, downtown, shopping mall) and temporal resolutions (i.e., day, week, month, and season). Movement signatures may vary based on spatial and temporal resolution. The encoding of movement signatures must include an adequate representation of the temporal dimension. Very fine spatial scale movements such as regular visits to the neighborhood pizza shop may be lost in a "home" signature without high-resolution spatial and temporal observations.

Large and relatively high frequency subsets of observations can begin to reveal movement signatures such as an animal tracing a similar path at similar times of the day. With large collections of unit observations, we can build summaries that describe movement patterns in the collection such as whether the movements are systematic, organized, regular, or periodic (Yuan, 1998). We identify two types of movement signatures of objects broadly: spatial and spatio-temporal signatures. Within each of these, we have also identified two further signature types location and path signatures as explained in the following sections.

3.2.1 Describing Signatures

A pattern is approximate in the sense that its instances may occur several times and they are usually similar but not identical. If you look at it another way, a movement signature is not black and white; it is present in a graded way (described as a fuzzy degree of truth by a number between 0 and 1) as will be shown in Chapters 4 and 5.

A movement signature can be qualitative in that it typically does not specify actual numeric values such as x–y position coordinates, distances, directions, time instants (or intervals) but deals with approximate (or abstract) linguistic values. Linguistic descriptors like downtown, short distance, northeast, afternoon, about 3 hours and so on replace numeric values.

In addition, a movement signature can be quantitative in that it typically does specify moving objects' positions, directions, and distances along with the travel time (duration) and periodicity of the movement using actual numeric values such as x–y position coordinates, and time instants (or intervals) that are obtained from a set of observations. A movement signature is derived from a combination of both qualitative and quantitative observations that specify moving objects' positions, directions, and distances along with the travel time (duration) using both actual numeric values that are obtained from a set of observations or the approximate linguistic values that are obtained from expert knowledge. A movement signature of an object may include both quantitative and qualitative descriptions of a movement as shown in Table 3.1 (Schlieder et al., 2001).

Table 3.1: Quantitative and qualitative descriptions of movements.

Quantitative description of a movement	Qualitative description of a movement
Position (x, y)	Position (home)
Orientation (63^{o})	Orientation (northeast)
Distance (100 meters)	Distance (nearby)
Direction (87^{o})	Direction (north)
Duration (22 hours)	Duration (day)

Position and orientation describe the outcome of movement, that is, the current location of the moving object and the direction it is moving. The other parameters give some information about the movement itself. Direction, distance, and duration of the movement are measured with respect to the previous unit movement. A relational algebra defined over {east, northeast, north, northwest, west, south, southwest, and southeast} allows expressing qualitative directions, whereas a relational algebra defined over {near, medium, far} describes qualitative description of a distance of the moving object from a certain reference location.

In this thesis, a movement signature is defined using the following attributes:

- Object ID: since it is associated with a particular object,
- Signature ID: since there can be more than one per object,
- Type: location signature or path signature,
- Order: primary, secondary, tertiary, and so on which changes based on the application and user requirements,
- Time descriptor (numeric-12.15 pm or linguistic-noon).

Remaining attributes are assigned depending on the application type (i.e., modeling the movements of couriers) and how a signature is derived (i.e., fuzzy c-means).

3.2.2 Approaches to Extract and Represent Movement Signatures

General or meaningful movement patterns of objects can be extracted by analyzing a set of movement observations. Detection of movement signatures of objects requires analysis of long-sequences of movement observations on an object. Frequently occurring patterns in the movement data can be summarized to identify repeated

movements (i.e., movements to and from work). Certain movements appear to have specific signatures based on spatial and temporal range, speed and other movement properties. These may be revealed through analysis of the observation data. This thesis proposes two different approaches to summarize observation data sets to extract movement signatures of objects.

The first approach described in detail in Chapter 4 proposes the use of clustering algorithms to summarize observation data sets in extracting spatial location signatures of an object. It assumes that if a spatial location signature is a group of data sharing similar values then data mining approaches such as clustering algorithms are generally well equipped to detect them. This approach proposes extracting spatial location signatures of an object from a set of position observations with no time information given. The approach uses clustering of position observations on an object. In order to carry out the proposed approach for obtaining spatial location signatures of objects, Fuzzy c-means (section 2.8.2) method is employed. By clustering the observed positions of a moving object, a set of fuzzy locations frequently visited by the object is identified. Each fuzzy location consists of a set of positions and their degree of memberships to the location. As an example, the fuzzy c-means clustering method was employed for the position observations given in Figure 3.4 and four fuzzy clusters were identified as shown in Figure 3.5. These four fuzzy clusters (fuzzy locations) on a movement surface are used for defining spatial location signatures of an object. Using this approach in Chapter 4, spatial location signatures are represented with fuzzy clusters (Table 4.2, Figure 4.4) and their corresponding fuzzy membership functions (Figure 4.6, Figure 4.7).

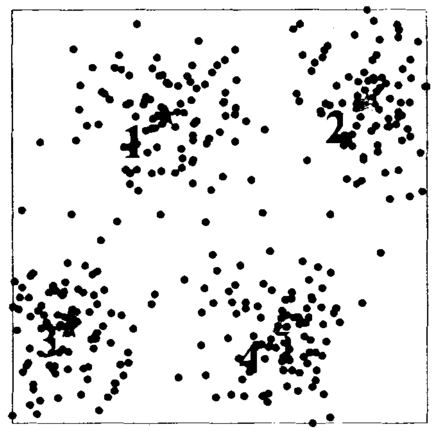


Figure 3.5: Fuzzy c-means clustering of the position observations.

The second approach described in detail in Chapter 5 is proposed to summarize large observation data sets in order to obtain spatio-temporal movement signatures of an object. Two additional movement parameters namely number of visits (z_i) and the time of the visits (t_i) to each fuzzy location are provided and used in the computation process of obtaining spatio-temporal movement signatures of an object. In this approach, movement surfaces are used to establish the locations that an individual moving object has visited over a time interval. These locations may be obvious through expert knowledge and visualization of the data but must be automated to offer real benefit. Using this approach, spatio-temporal movement signatures are defined as matrices and represented as surfaces (Figure 5.3) or volumes (Figure 5.9).

The approaches proposed in this thesis for the development of movement signatures of objects can be distinguished primarily as:

- Quantitative Approaches (Signatures obtained using specifically fuzzy (i.e., fuzzy c-means) and neuro fuzzy methods (i.e., Anfis)).
- Qualitative Approaches (Signatures obtained using specifically fuzzy membership functions and rules).

3.2.3 Types of Signatures

As indicated, two types of movement signatures of objects are identified broadly:

- Spatial signature: the signature that has no time information related to the movement behavior of the object that it is assigned to.
- Spatio-temporal signature: the signature that has both space and time information related to the movement behavior of the object that it is assigned to.

Within each of these, two further signatures are also identified:

- Location Signature: a location that a moving object frequently or typically visits such as home, work, and shopping location.
- Path Signature: a path that an object usually moves on specifically the connected set of location signatures such as the path to work or the path of a city bus.

By summarizing movement observations of an object, we can describe the locations they usually visit, the paths they usually move in, and potentially the general time frames in which these general movement patterns occur. As an example, the identified four locations shown in Figure 3.6 are referred to as the location signatures and the paths that connect these four locations to each other are referred to as the path signatures of the moving object.

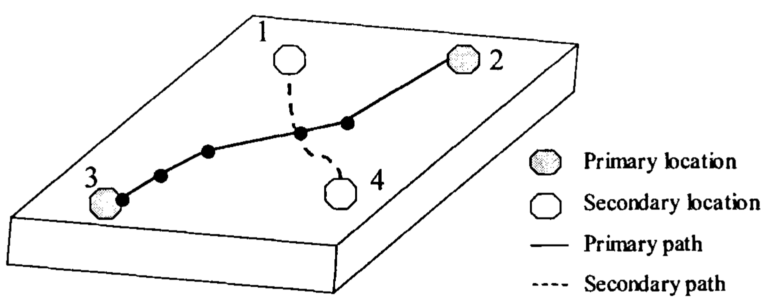


Figure 3.6: Movement signatures.

3.2.4 A Fuzzy Logic Approach to Represent Movement Signatures

Reasoning in geographic space typically deals with incomplete and imprecise information, but people can frequently draw sufficiently precise conclusions based on common sense. A number of cognitive studies provide evidence that people may employ hierarchically organized schemes to reason in geographic space and to compensate for missing information (Egenhofer and Mark, 1995; Hirtle and Jonides , 1985; McNamara et al., 1989). Therefore, it is very important to find out how people conceive and describe movements of objects.

Many parameters and variables in movement modeling are characterized by uncertainty, subjectivity, and imprecision. Human experts are usually able to provide certain linguistic information about movements of objects. However, they are usually not able to give their knowledge, experience, and intuition in terms of linguistic information alone. Linguistic information is supplemented by certain numerical information obtained from measurements, observation, or statistical analysis of movements of an object. Both numerical and linguistic information in the design process of fuzzy membership functions related to the movement signatures of objects is considered in this thesis.

Fuzzy sets are used to associate quantitative information with qualitative information. A linguistic location (i.e, Orono) can be defined by the coordinates of its minimum bounding rectangle $MBR = \{(x_1, y_1), (x_2, y_2)\}$. For example, a set of positions $\phi = \{A_{(x_1,y_1)}, B_{(x_2,y_2)}, \ldots, K_{(x_n,y_n)}\}$ (Figure 3.7) visited by a moving object over time can be associated with the linguistic value "Orono".

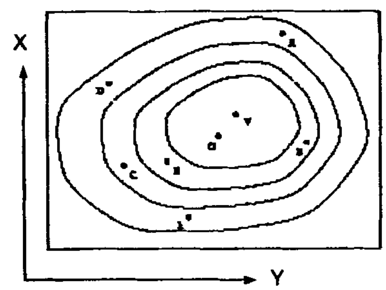


Figure 3.7: MBR of linguistic location "Orono".

The linguistic location "Orono" can be represented with associated fuzzy membership functions that bound its MBR as shown in Figure 3.8.

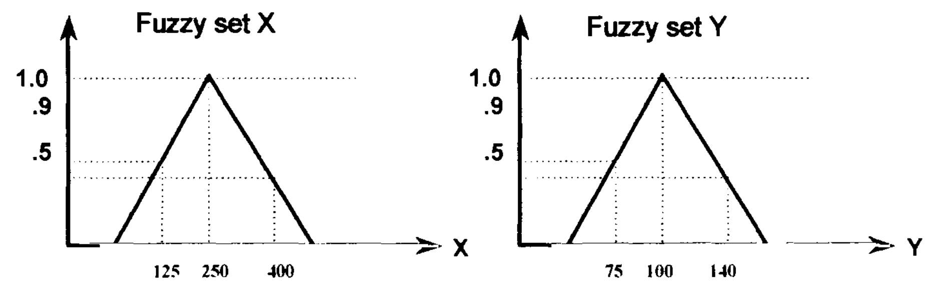


Figure 3.8: X and Y fuzzy membership functions of MBR of Orono.

In addition, any position that is within this MBR is represented with an associated value of degree of membership to the fuzzy set. Therefore the set of positions $\phi = \{A_{(x_1,y_1)}, B_{(x_2,y_2)}, \ldots, K_{(x_n,y_n)}\}$ can be represented within the fuzzy set "Orono" (equation (3.3)) such that each coordinate pair represents a position in "Orono" with an associated fuzzy value as shown in Figure 3.9. For example, position E is represented with an associated fuzzy membership value of $E = 0.8$ within the fuzzy set "Orono". The fuzzy set "Orono" that represents a set of positions is referred to as the "**fuzzy location**" and represented with the fuzzy set μ_{Orono} as given in equation (3.3).

$$\mu_{Orono} = \{(A,0.9),(E,0.8),(C,0.4),\ldots\ldots.(..)\} \tag{3-3}$$

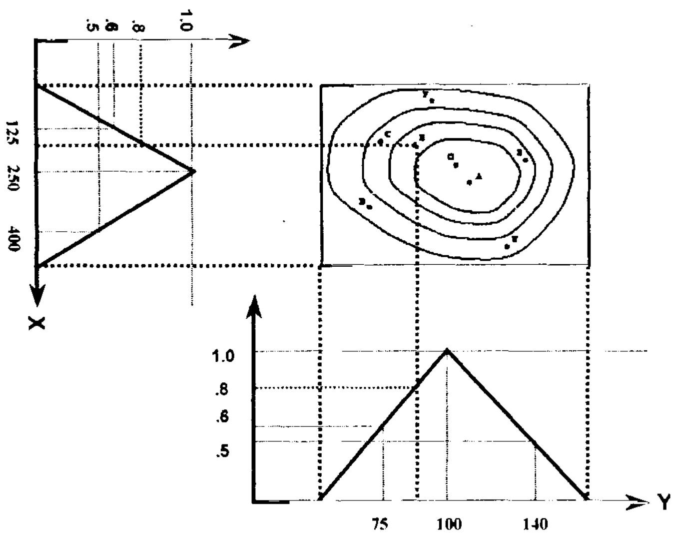


Figure 3.9: Fuzzy set "Orono".

Similarly, a connected set of locations $\Lambda = \{L_{1(x_1,y_1,t_1)}, L_{2(x_2,y_2,t_2)}, \ldots, L_{n(x_n,y_n,t_n)}\}$ visited by a moving object over time is referred to as a "path" of the moving object (Beard and Palancıoglu, 2000; Dorst et al., 1991; Jan et al., 2000). As we demonstrated above, each of these visited locations can be represented with an associated fuzzy location (i.e., μ_{Boston} and μ_{Orono}). Therefore, we can say a path connects a set of fuzzy locations to each other. Such a path taken by the moving object over time is referred to as the **fuzzy path**, and associated with an appropriate fuzzy value such as "I-95" or "Boston-Orono". A fuzzy path can be represented with a set of fuzzy locations as given in equation (3.4).

$$\mu_{path} = \{\mu_{L_1}, \mu_{L_2}, \ldots\ldots, \mu_{L_n}\} \tag{3-4}$$

For example, the fuzzy path that connects Boston, MA to Orono, ME can be represented as a collection of fuzzy locations as given in equation (3.5).

$$\mu_{Boston-Orono} = \{\mu_{Boston}, \mu_{Portland}, \mu_{Waterville}, \ldots\ldots, \mu_{Orono}\} \tag{3-5}$$

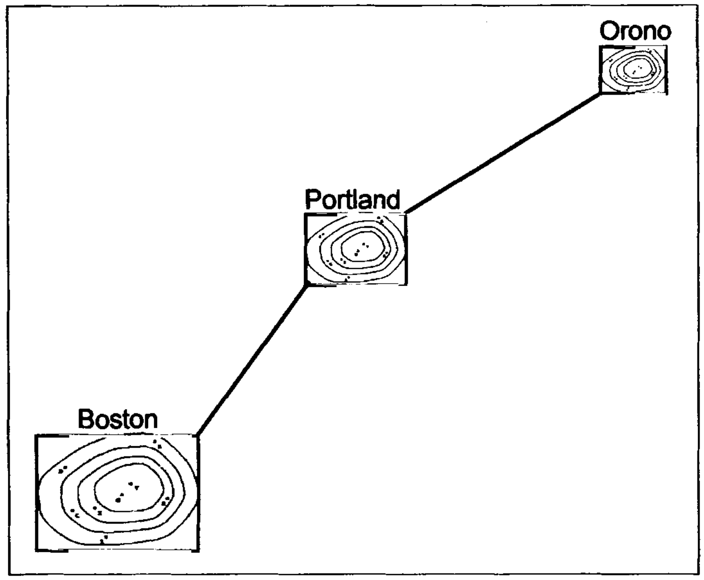


Figure 3.10: Fuzzy path "Boston to Orono".

By clustering the observed positions of a moving object, a set of fuzzy locations frequently visited by the object can be identified. This set of fuzzy locations is referred to as the **location signature** of the moving object. Each obtained cluster is composed of the observed positions of a moving object and represents a fuzzy location. Cluster centers for each fuzzy location are represented with a degree of membership of 1.00 to its corresponding cluster. For each position in a cluster, a membership degree (fuzzy value) to this cluster is assigned (i.e., for the position (x_1, y_1) the fuzzy value = 0.9 is assigned for cluster # 1). For example, a position (x_2, y_2) that is in the downtown Bangor has a degree of membership of 0.95 to the fuzzy set Bangor whereas a position (x_3, y_3) that is in the Bangor Mall has a degree of membership of 0.65.

Similarly, a set of fuzzy paths used frequently by a moving object over time and connecting a set of fuzzy locations to each other is defined as a **path signature** of the moving object.

This thesis compares locations and paths visited and taken respectively by a moving object over time primarily based on number of visits (z_i) to each location or path by a moving object. Number of visits to locations or paths by a moving object is important information in extracting movement signatures of the object. The total number of visits to each location or path over time is the basic parameter that influences the strength of the hierarchy in determining the dominant locations and paths used by a moving object.

Location and path signatures can be represented in a hieratical order as shown in Figure 3.6 based on how frequently locations and paths are visited by a moving object as shown in Figure 3.11. Location signatures can be represented in a hieratical order that includes primary locations: locations a moving object visits most frequently (i.e., home and work locations), secondary locations: locations a moving object visits less frequently (i.e., shopping locations), and so on. Similarly, path signatures can also be represented in a hieratical order that includes primary paths: connections between primary locations (i.e., a path between home and work), secondary paths: connections between secondary locations or primary/secondary locations (i.e., shopping paths).

A fuzzy reasoning algorithm that uses membership functions of number of visits and order index was developed in Chapter 5 to determine a hierarchical structure for the signature embedded in the spatio-temporal signature definition matrix of an object. Using the fuzzy reasoning algorithm, all z_i values corresponding to each location in the signature definition matrix are characterized by a corresponding order index value, which varies from 0 to 1 (see section 5.3.3).

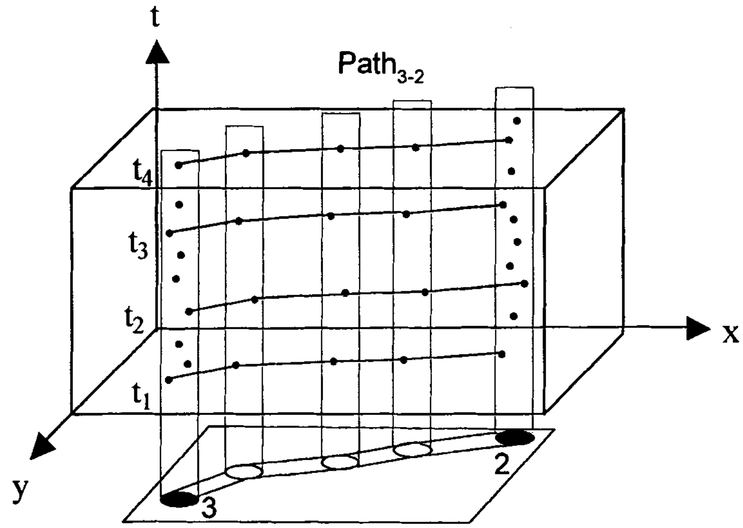


Figure 3.11: Visit frequency of a path connecting location 3 to 2.

Chapter 4

APPROACHES TO EXTRACT SPATIAL LOCATION SIGNATURES BY CLUSTER ANALYSIS

Larger and larger volumes of raw position observations are being collected and methods are needed to manage and analyze these in terms of movement patterns. There are currently few geographical analysis methods capable of exploring large databases for detecting and summarizing movement patterns. As a result many important datasets are not being analyzed to the fullest extent. For example, data about movements of animals, city buses, and criminals are collected and analyzed, if indeed at all, using inadequate methods and this implies need for data mining techniques.

This chapter describes approaches for deriving spatial location signatures for an object. The objective is to capture the locations that are frequently visited by a moving object using a set of observations. A set of movement observations, which consists of a set of positions (x_i, y_i), is analyzed to derive spatial location signatures. In this chapter, temporal information related to the observations is ignored.

In the analysis of the observations, a data mining method to find clusters and patterns in observations is employed. Classification of movement observations into signatures can be handled by using clustering methods. In this thesis, fuzzy c-means clustering (FCM) is used to derive the spatial location signatures of objects from movement observations. From the results of FCM, a set of locations and their corresponding fuzzy membership functions are obtained to represent spatial location signatures of objects.

4.1 The Proposed Method

The proposed method to derive spatial location signatures of an object is structured as shown in Figure 4.1. More detail on the method is provided through out the remainder of the chapter.

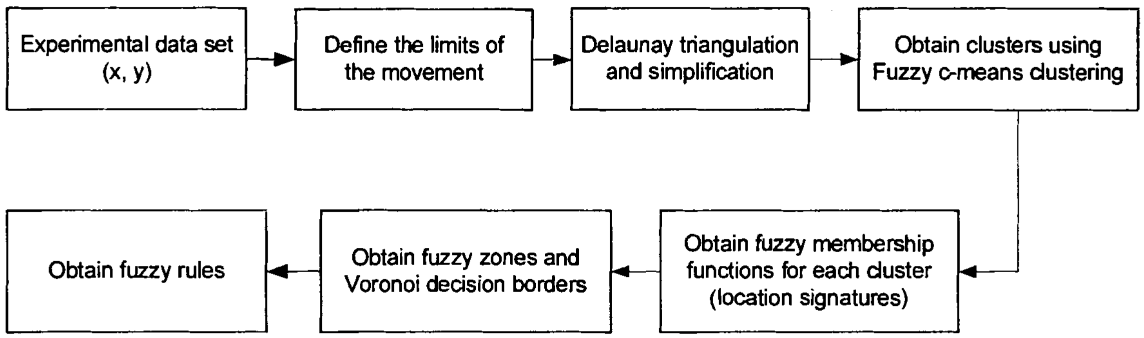


Figure 4.1: Approaches to extract spatial location signatures.

4.2 Experimental Data Set

A synthetic data set is used as the observation data set in the extraction of spatial location signatures for a moving object θ. The observation data set consists of a set of approximately 2000 positions (x_i, y_i) as shown in Table 4.1. Figure 4.2 illustrates the study area and the set of synthetic position observations used in this study.

Table 4.1: The Observation Data Set.

Observation ID	X	Y
1	252.1298	155.1223
2	80.8776	370.1234
....	....	....
1345	243.2976	173.3283
....	....	....
N	X_n	Y_n

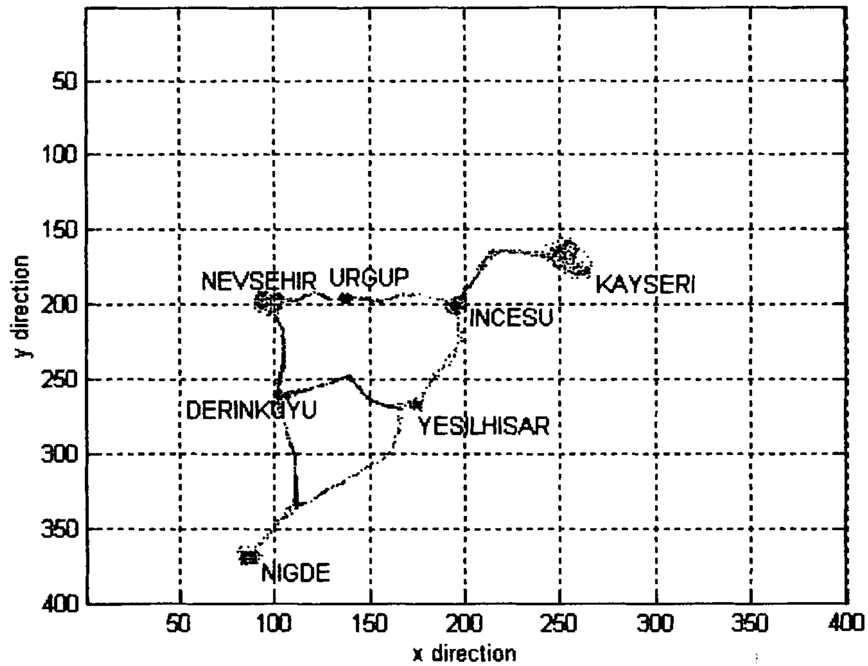


Figure 4.2: The study area and observed positions.

Figure 4.2 demonstrates that observed positions are spread over a wider geographic area than the data that belong to certain paths such as highways linking two different locations to each other. Each location can be represented with its boundary such as MBR= {(X_{min}, Y_{min}) and (X_{max}, Y_{max})} and an identifying label such as Bangor. In other words, a location is an area that has a boundary (i.e., its cluster boundary or MBR) and may or may not contain a set of positions.

In order to define the limits of the observed movements of an object in the study area a Delaunay triangulation is constructed. The Delaunay triangulation network consisted of 2575 triangles and was simplified to 2246 triangles as shown in Figure 4.3. The Delaunay triangulation network and corresponding Voronoi polygons are used in the clustering and classification of movement data as explained in the following sections.

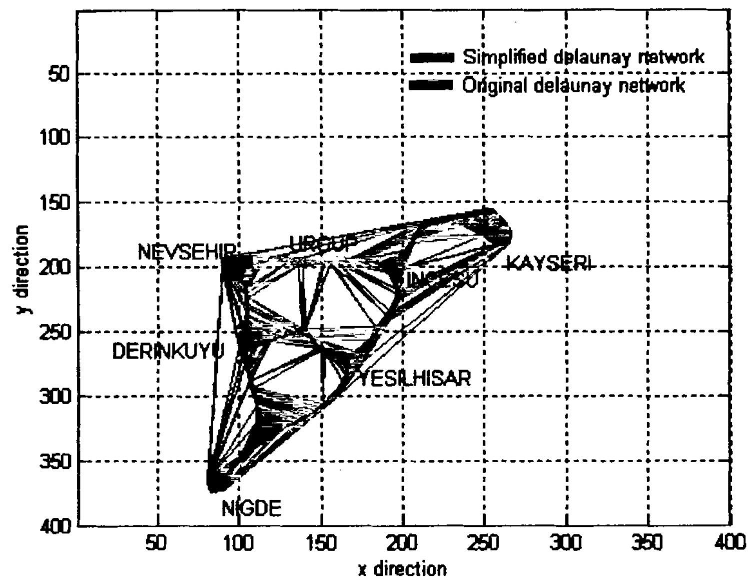


Figure 4.3: Original and simplified Delaunay network.

4.3 The Approach: FCM Clustering to Obtain Movement Signatures

This approach assumes that if a movement signature is a group of data sharing similar values related to locations and paths of a moving object then a clustering algorithm can detect them. In other words, classification of movement observations into signatures can be handled by using a clustering method. In order to carry out our proposed approach for obtaining movement signatures of objects, the Fuzzy c-means clustering method is employed. Please refer to section 2.7.2 of this thesis for detailed information about the method. Using this approach, movement signatures are represented with fuzzy clusters and their corresponding fuzzy membership functions.

By clustering the observed positions of a moving object, a set of fuzzy locations frequently visited by the object can be identified. This set of fuzzy locations is referred to as the **spatial location signature** of the moving object. Here, the observation data in the study area are clustered to 10 clusters using fuzzy c-means algorithm. The corresponding cluster centers (Table 4.2) and clusters (Figure 4.4) are obtained.

Table 4.2: Fuzzy cluster center coordinates.

Cluster Center IDs	X	Y	Cluster Center IDs	X	Y
1	138.7874	196.0873	6	111.2976	299.6382
2	137.7176	251.6073	7	100.1271	199.7644
3	167.2341	267.3869	8	87.1394	367.3287
4	197.2379	196.6703	9	115.2863	327.7724
5	106.7128	254.9292	10	251.0394	169.2004

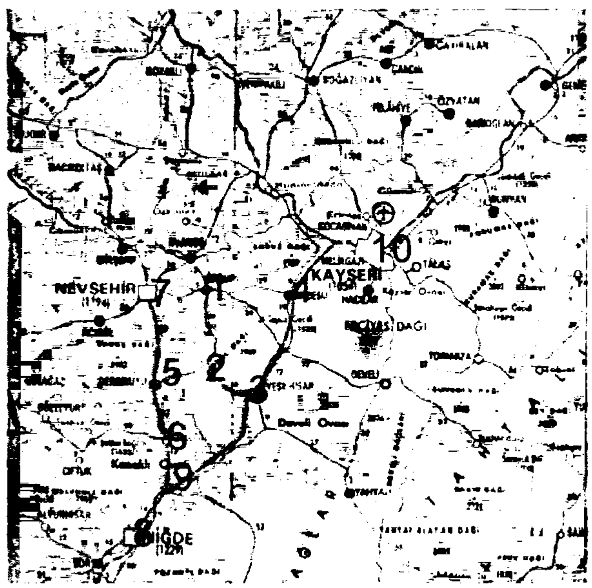


Figure 4.4: Fuzzy c-means classifier results of simulated data.

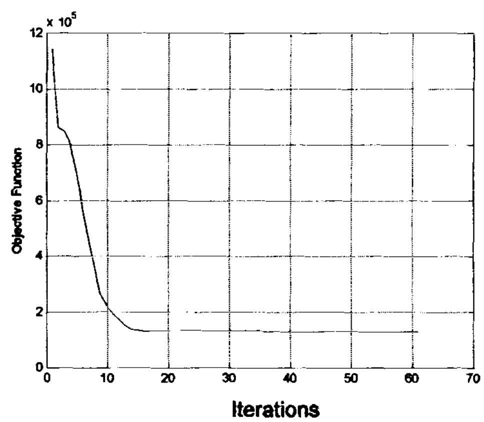


Figure 4.5: Number of iterations to be carried out during the fuzzy c-mean clustering.

In the FCM clustering process, the maximum number of iterations to be carried out is taken as 100 iterations. However, the distances between the clusters met the threshold after 61 iterations (Figure 4.5).

Another parameter whose value needs to be determined in fuzzy clustering is the weighting exponent m. The weighting exponent controls the extent of membership sharing between fuzzy clusters in the data set. In this study, the value of the weighting exponent was m=2. For the computation procedure of the FCM clustering method please refer to (Emami et al., 1996).

This thesis defines a **fuzzy location** as a location in which a degree of membership (fuzzy value) for each position within the location has been computed and assigned. The obtained 10 clusters are therefore referred to as fuzzy locations visited by the moving object θ. The obtained 10 fuzzy locations and their degree of membership values along with their center coordinates are given in Table 4.3. As can be seen from Table 4.3, each cluster is composed of a number of positions visited by a moving object.

As we mentioned before, each location is represented with its fuzzy boundary. In this case fuzzy cluster boundaries are used as the boundary of each cluster (location) and their corresponding cluster numbers are assigned an identifying label such as cluster # 10 (the city of Kayseri). The center of a location can be represented with either its fuzzy cluster center coordinates as shown in Table 4.2 or its MBR center coordinates given in Table 4.4 as explained in section (3.2.4) of this thesis.

Table 4.3: Fuzzy Clusters and their MF values.

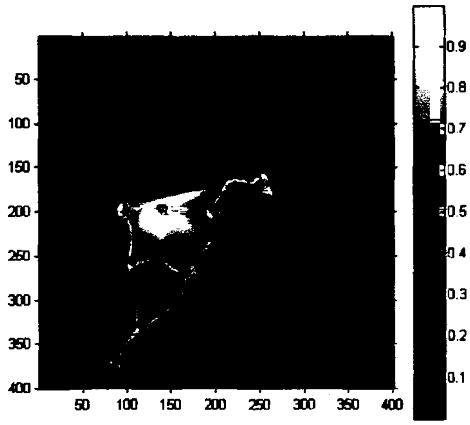
Cluster Center ID	X	Y	μ_L
1	138.7874	196.0873	1.00
Observation ID	X	Y	μ_L
1653	185.1612	195.6613	0.87
118	189.2301	198.0703	0.78
.....	.....	.....	.....
1562	183.2641	197.8192	0.97
.....	.....	.....	.....
Cluster Center ID	X	Y	μ_L
10	251.0394	169.2004	1.00
Observation ID	X	Y	μ_L
1345	243.2976	173.3283	0.93
1418	250.1271	180.1614	0.65
.....	.....	.....	.....
1336	87.1394	367.3287	0.94

Table 4.4: MBR of the clustered locations.

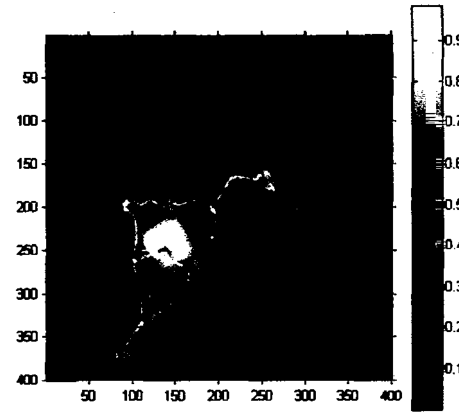
Location IDs	Location Labels	X_{min}	Y_{min}	X_{max}	Y_{max}
1	Urgup	130	200	140	190
2	Kodul dagi	180	255	190	245
3	Yesilhisar	160	275	185	265
4	Incesu	185	215	205	185
5	Derinkuyu	95	270	115	255
6	Golucuk	110	295	115	290
7	Nevsehir	80	215	110	185
8	Nigde	80	375	90	360
9	Konakli	110	345	120	330
10	Kayseri	235	180	270	155

The cluster centers for each fuzzy location are represented with a degree of membership of 1.00. And for each position in a cluster, a membership degree (fuzzy value) to the cluster is assigned as given in Table 4.3. For example, the position # 1345 with the coordinates x_{1345}=243.2976 and y_{1345}=173.3283 is assigned to cluster # 1 and assigned label "city of Kayseri" with the fuzzy membership value of $\mu_{1345} = 0.93$.

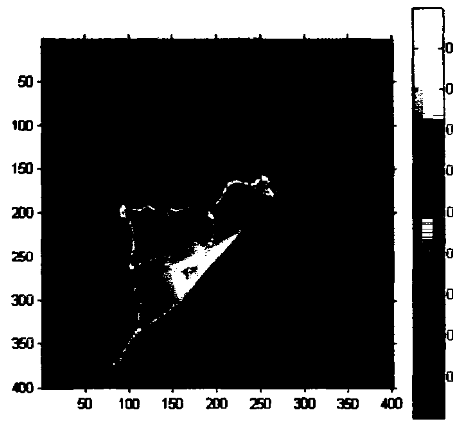
Using fuzzy c-means clustering method over the observation data, spatial location signatures are represented with fuzzy clusters (Figure 4.4, Table 4.3) and their corresponding fuzzy membership functions. The corresponding membership functions of each fuzzy cluster, which are also the spatial location signatures, are computed (Table 4.3) and illustrated in Figure 4.6i-j. The membership function for the cluster and the location # 10 is illustrated in Figure 4.7a. Similarly, the membership functions for all the clusters and locations are transparently illustrated in Figure 4.7b.



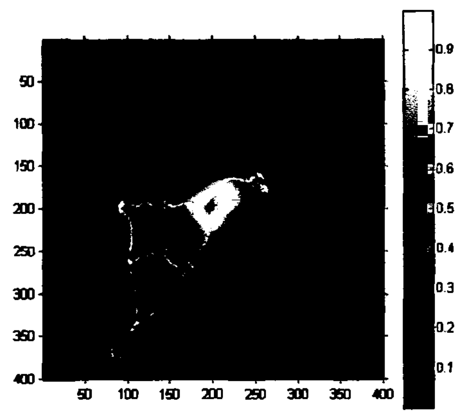
(a) MF of the 1st fuzzy cluster



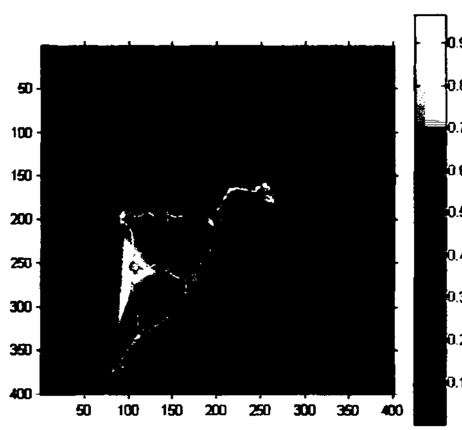
(b) MF of the 2nd fuzzy cluster



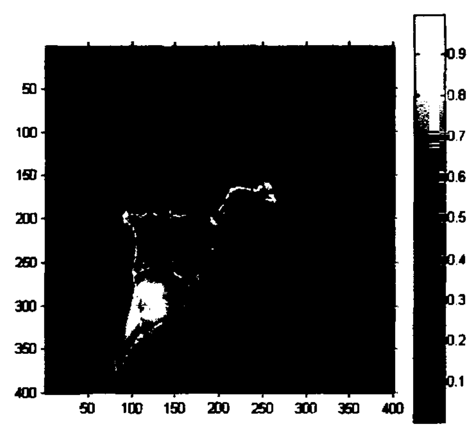
(c) MF of the 3rd fuzzy cluster



(d)MF of the 4th fuzzy cluster

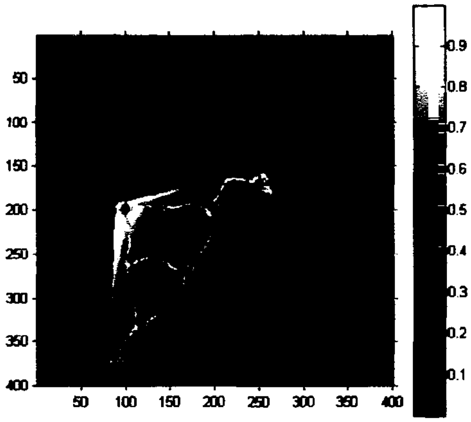


(e) MF of the 5th fuzzy cluster

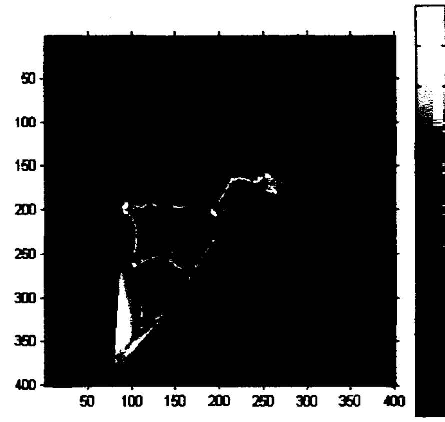


(f) MF of the 6th fuzzy cluster

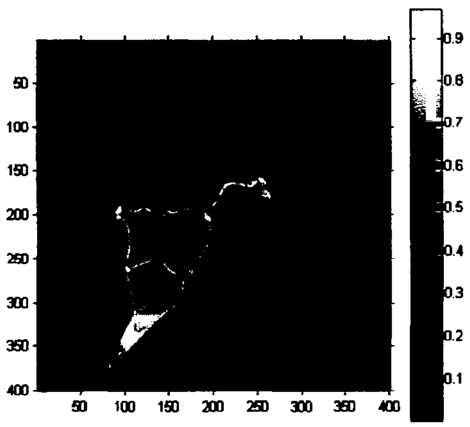
Figure 4.6: MF of each fuzzy cluster based on the Delaunay triangle borders.



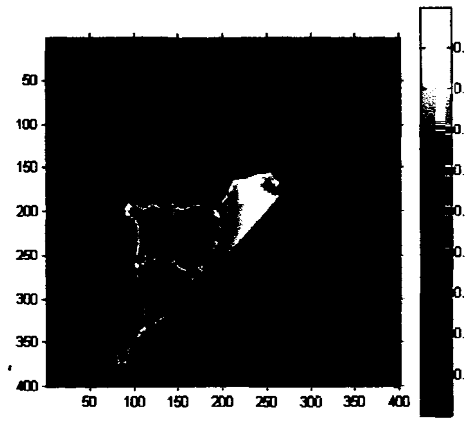
(g) MF of the 7th fuzzy cluster



(h) MF of the 8th fuzzy cluster

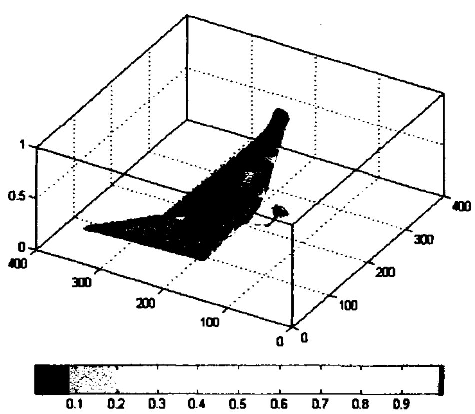


(i) MF of the 9th fuzzy cluster



(j) MF of the 10th fuzzy cluster

Figure 4.6: Continued.



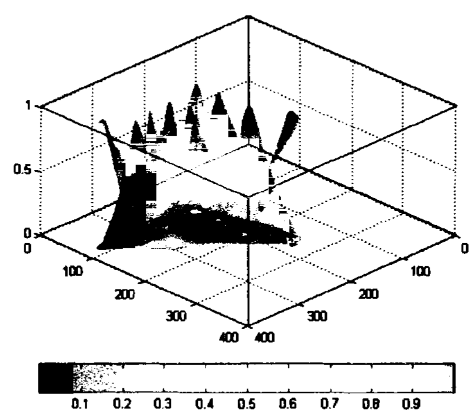


Figure 4.7: (a) MF for the cluster and the location number 10 (b) Transparently illustrated MF hills for all the clusters and locations (spatial location signatures for each location).

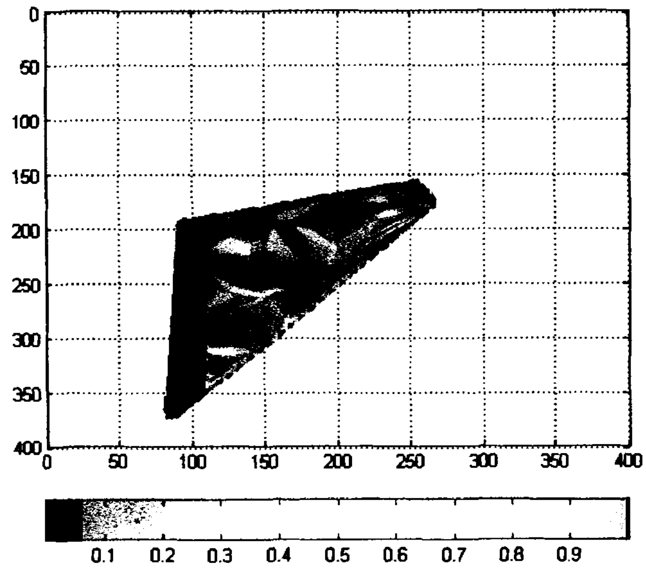


Figure 4.8: The top view of MFs hills for all the clusters and locations.

In addition, the top view of MFs hills for all the clusters and locations is shown in Figure 4.8. In Figure 4.9, the fuzzy zones of each cluster are obtained by imposing the MF values given in Figure 4.6. The fuzzy zones are computed according to the distance coordinate values of FCM clusters. The evaluation of the membership function values needs to be done jointly in the FCM. Therefore, all the membership functions given in Figure 4.6 are evaluated jointly and the fuzzy cluster zones are computed via FCM as illustrated in Figure 4.9.

For each cluster, a Voronoi polygon is computed and named as the decision zone for the corresponding cluster. A decision zone defines the bounds of each location such as borders of a city. The decision zones shown in Figure 4.10 are generated if the observation data are classified to 10 clusters using the cluster center coordinates of the fuzzy c-means clusters. These zones provide the ability to make decisions about locations in which the moving object is present based on fuzzy rules.

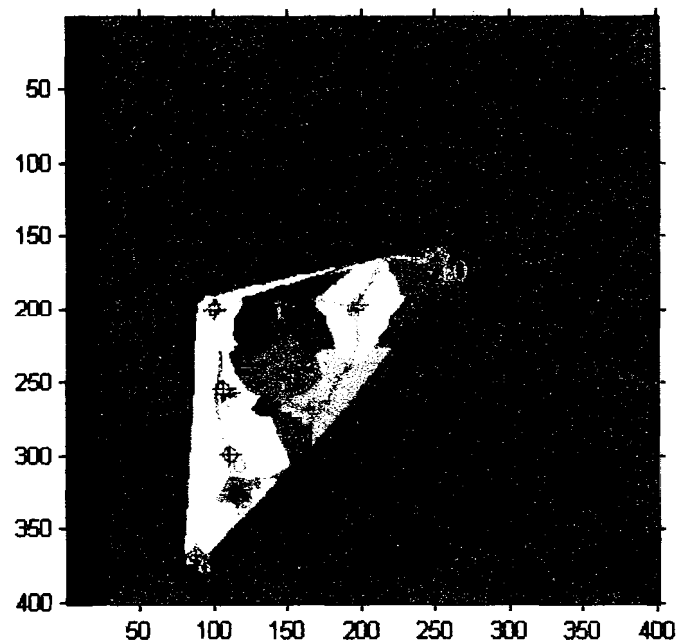


Figure 4.9: Fuzzy cluster zones.

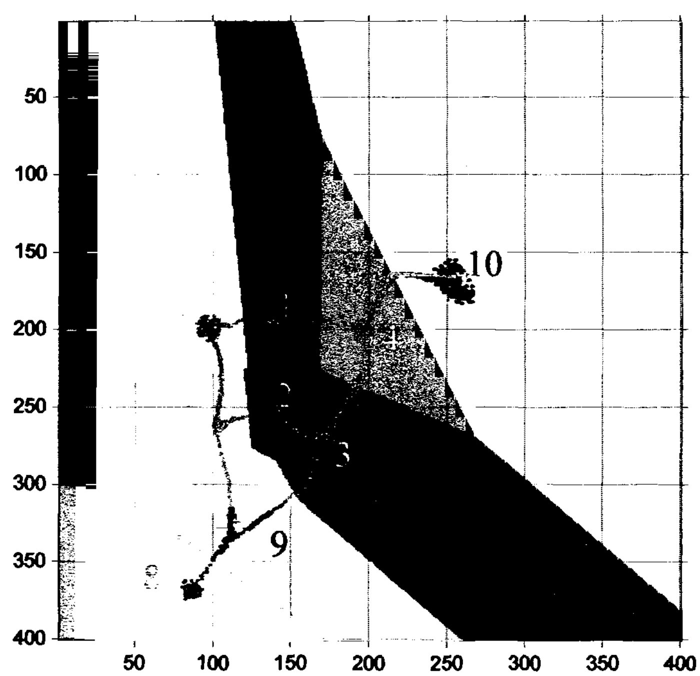


Figure 4.10: Voronoi decision zones of locations.

The truth-value of a fuzzy rule created by the structure given in equations (4.1) and (4.2) can be assessed using the decision zones based on x and y coordinate parameters. The obtained results can be used in computing the weight of the fuzzy rule.

Fuzzy Rule # 1 "If the object θ is observed in a x_i - y_i position, then the object θ is in the i^{th} decision zone (location signature rule)." (4-1)

Fuzzy Rule #2 "If the object θ is observed on the path defined with a set of x_i and y_i positions, then the object θ is in the decision zone defined with the largest membership value of the μ_{path} which is given in equation (4.3) (path signature rule)." (4-2)

The truth-value of a fuzzy rule created by the structure given below can be assessed using the decision zones based on x-y parameters and obtained results can be used in computing the weight of the fuzzy rule. Therefore, decision zones can be used in analyzing the truth-values of fuzzy rules and in computing the weights of these rules. And the fuzzy rules can be examined for path and location signatures. If a path goes through more than one decision zone, lengths of each path section in each zone can be used in computing the weight of the fuzzy rule. As an example, if the path signature structure is defined using the membership function, μ_{path_i}, for the object θ that is moving from location A to location B, the equations (4.3) and (4.4) can be given.

$$\mu_{path_i} = \frac{S_i}{\sum S} \quad i = 1,2....,n \tag{4-3}$$

$$\sum S = S_1 + S_2 + ... + S_n \tag{4-4}$$

where n is the number of decision zones, $\sum S$ is the sum of path length, and S_i is the length of the path inside the i^{th} decision zone.

Chapter 5

APPROACHES TO EXTRACT SPATIO-TEMPORAL MOVEMENT SIGNATURES BY SUMMARIZATION

Moving objects have changing and repeating patterns due to their movement in space over time (Mountain and Raper, 2001b; Schlieder et al., 2001). A set of observations on a moving object can be used to derive the movement patterns of an object by summarizing frequently visited locations and frequently used paths over time by the object. These space and time dependent movement patterns of an object are referred to as **spatio-temporal movement signatures** in this thesis. There is a need to understand and identify the spatio-temporal movement signatures of a moving object. Analysis of the spatio-temporal movement signatures of an object can help improve modeling, querying, and reasoning capabilities of the movements of the object. A spatio-temporal movement signature should characterize the predominant patterns with respect to time of a moving object such that it can be distinguished from other moving objects.

Chapter 4 developed an approach to derive spatial location signatures of an object from a set of position observations with out consideration of the time information. The fuzzy c-means clustering was applied to the observations. By clustering the observed positions of a moving object, a set of fuzzy locations frequently visited by the object was identified. Each fuzzy location consists of a set of positions and their degree of memberships to the location.

This chapter describes an approach to extract spatio-temporal movement signatures of the moving object such as frequently visited locations (i.e., Boston, home,

and downtown) and frequently used paths (i.e., roads, railways, and lakes) over time by the object using the fuzzy locations obtained as explained in Chapter 4. Two additional movement parameters namely number of visits (z_{t_i}) and the time of the visits (t_i) to each fuzzy location are provided and used in the computation process of obtaining spatio-temporal movement signatures of an object. The number of visits per time interval (i.e., a month) can be obtained explicitly by computing the number of positions in each fuzzy location such as 36 positions in the fuzzy location "Kayseri" refers to the 36 visits to the location "Kayseri" (see Chapter 4).

In the proposed approach, spatio-temporal movement signatures of the object are treated as a surface, as a volume, or as a fuzzy membership function. A series of methods including conventional, fuzzy, and neuro-fuzzy methods to generate movement surfaces, volumes, and fuzzy membership functions from spatio-temporal movement observations to extract spatio-temporal movement signatures of an object are developed.

5.1 The Proposed Method

The proposed method of this chapter to define movement signatures of an object is structured as shown in Figure 5.1. More detail related to the methodology is provided through out the remainder of the chapter.

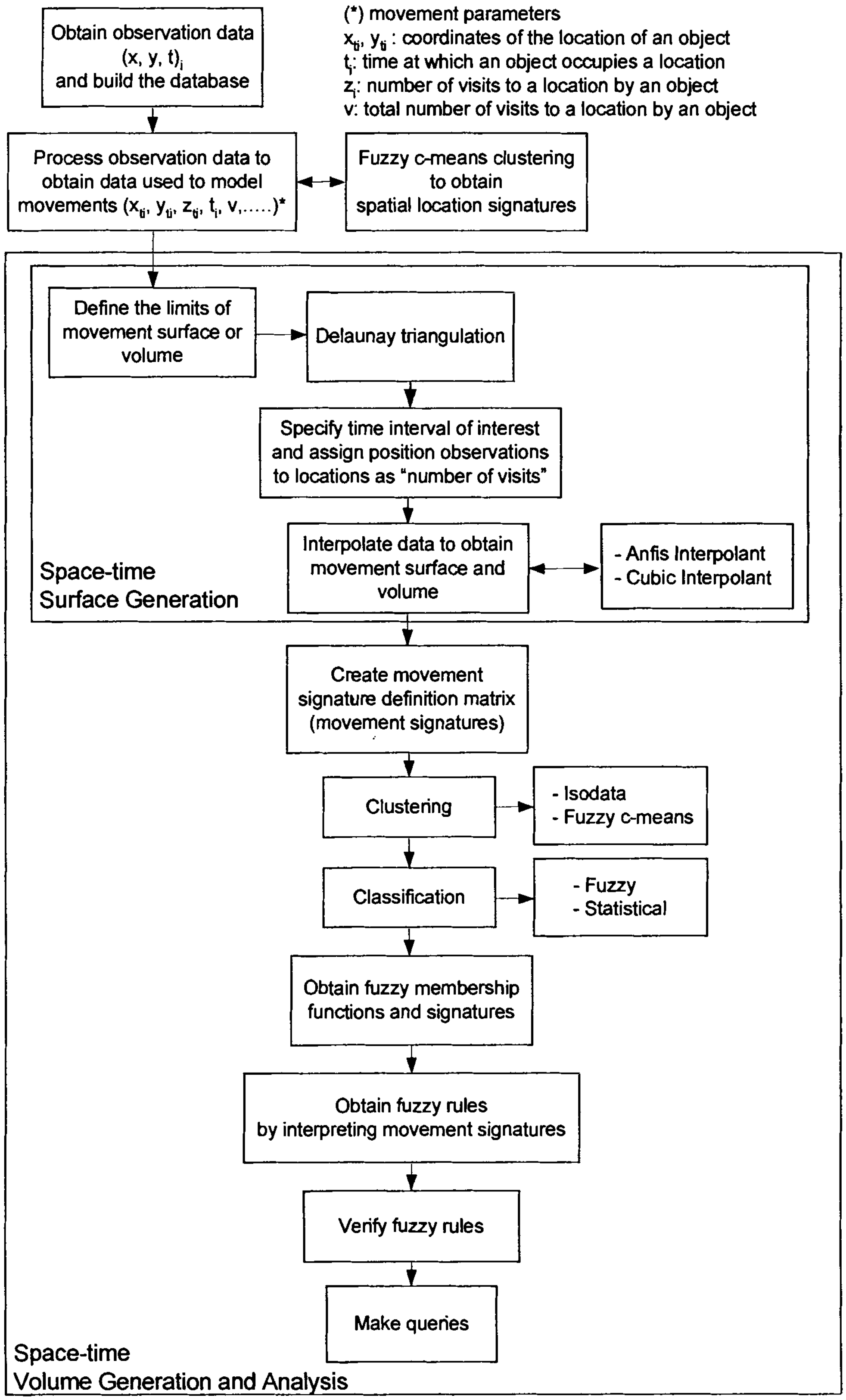


Figure 5.1: The proposed approach to extract spatio-temporal movement signatures.

5.2 Experimental Data Set

The approach to movement behavior modeling of a moving object starts with obtaining movement observations and related movement parameters (Figure 5.1). To illustrate the theoretical approach to obtaining spatio-temporal signatures of moving objects, we use an experimental data set that consists of a set of observation data representing positions collected on an object that visited 10 different locations (assigned using methods of Chapter 4). The number of visits (z_{t_i}) by the object to each location (i.e., city of Kayseri or cluster #10) is determined through out the t time domain as shown in Table 5.1. For this example, observations are organized according to 12 different time intervals t_i in this case corresponding to months.

Table 5.1: Observation data organized by number of visits per month to 10 different fuzzy locations.

			Monthly Observations (z_{t_i} ; i =1,2,3,..,12)												
Location ID#	X	Y	1	2	3	4	5	6	7	8	9	10	11	12	Total number of visits
1	5	94	4	4	3	2	3	3	5	4	3	4	4	4	43
2	6	6	1	0	0	0	0	0	0	0	0	1	1	0	3
3	25	48	17	18	30	40	59	79	64	34	25	21	16	17	420
4	49	77	14	16	27	39	54	58	51	40	26	16	16	14	371
5	54	24	4	4	8	12	13	14	8	5	5	3	4	3	83
6	82	96	1	0	1	2	2	3	2	1	1	0	0	1	14
7	89	9	19	22	19	15	13	17	24	28	22	20	19	16	234
8	78	66	18	21	57	68	55	48	36	27	18	16	16	19	399
9	45	1	18	16	12	7	6	9	11	15	22	22	18	16	172
10	34	96	14	10	17	31	42	36	26	21	14	12	13	14	250
Total number of visits			110	111	174	216	247	267	227	175	136	115	107	104	

The set of locations (Table 5.1) used in this experimental study in the computation of spatio-temporal location and path signatures forms a surface $D_{(x,y,z)_{t_i}}$, which is the movement surface, as shown in Figure 5.2a. The limits (x, y) of the movement surface $D_{(x,y,z)_{t_i}}$ in which computations are made is bound by the extent of the observation values.

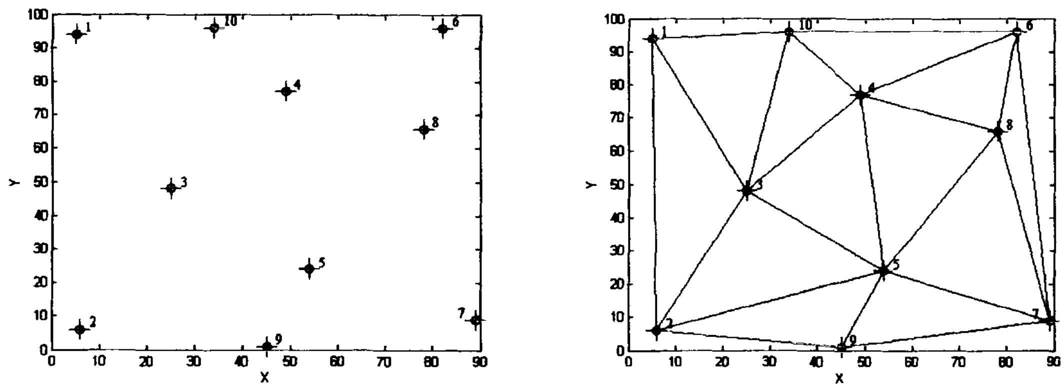


Figure 5.2: (a) The location signatures (fuzzy locations) and (b) The Delaunay triangles connecting the signature locations to each other.

If we assume a uniform space-time surface or volume and no constraints on an object's movements, a set of observed positions can be used to compute an object's probable path between observations or a position at any unmeasured space-time coordinate. As noted in the model framework of the proposed approach (Figure 3.1), movement signatures of objects can be represented using surfaces, volumes, mathematical expressions, and fuzzy membership functions and rules.

Before summarization of the movement data, we can gain an understanding of the movement data using visualization. Visualization is a useful tool for providing insight into geographic data sets (i.e., movements of objects) and can be used to explore the movement observations of an object over time and space. Volumetric visualization

techniques can be used in the analysis of movement behaviors of the objects. The perception of changes in the observed movement parameters is facilitated with a data visualization approach. Visualization supports the extraction of meaningful features from large data sets by summarizing the data points into meaningful groups and exposing regions of interest by data reduction and compaction.

Delaunay triangulation is commonly used for generation of surfaces from scattered points (Chiyokura, 1986). The Delaunay triangulation is used to create a structure for the interpolation of movement observations at unobserved locations on the movement surface as shown in Figure 5.2b.

5.3 Spatio-temporal Location Signatures

The spatio-temporal location signatures of an object are computed based on the number of visits to identified locations throughout the t domain and represented with a $D_{(x,y,z)_{t_i}}$ surface or a $V_{(x,y,z)_{t_i}}$ volume. To compute spatio-temporal location signatures of an object θ moving on a $D_{(x,y,z)_{t_i}}$ surface or in a $V_{(x,y,z)_{t_i}}$ volume the following steps are addressed.

- Classification of the $D_{(x,y,z)_{t_i}}$ surface based on number of visits to each location by a moving object θ.
- Finding the probable location of a moving object θ on a $D_{(x,y,z)_{t_i}}$ surface or in a $V_{x,y,z_{t_i}}$ volume at any t_i time interval, in this case at the resolution of months, using a neuro-fuzzy method.

5.3.1 Movement Surface Generation

Surface generation techniques (Barnhill, 1983; Farin, 1990) employ a variety of estimation/interpolation methods (Chiyokura, 1986), which may be classified according to the type of data used, the form of the 'interpolant' or fitting function, and the form of the average weighting used (Franke and Nielson, 1990; Okade et al., 1992). There are various approaches developed for surface description using scattered data sets (Barnhill, 1983; Farin, 1990; Franke, 1982). In this thesis, the visited locations are used to develop $D_{(x,y,z)_{t_i}}$ surfaces for the 12 month-intervals as shown in Figure 5.3.

The development of the spatio-temporal signatures considers changes in the behaviors of an object θ over time (at different levels of temporal resolution). From a set of observations we know that the object θ has visited a set of fuzzy locations. The number of visits (z_{t_i}) to each fuzzy location by the object θ forms the basis for determining the expected number of visits to an unknown location for the object θ by interpolating the observed z_{t_i}.

Because movement data cannot be obtained continuously, one needs to interpolate the observation data that are obtained in discrete form. When dealing with sets of observed positions, one can apply interpolation between observations to estimate the movement. This thesis uses two different interpolation methods, namely Cubic and Anfis interpolant, for estimating movement surfaces and volumes based on the observation data.

The primary concern of this thesis in choosing an interpolation method was construction of valid surfaces. The Cubic interpolant is a triangular interpolant that uses the piecewise cubic Hermite interpolation to interpolate positions, normals, and surface

curvature at the vertices of a triangle. Extensive literature regarding how the cubic interpolant can be used to approximate known functions, including algebraic surfaces and offset surfaces is available (Crain, 1970; Elvins, 1992; Gallagher, 1995).

Interpolation plays a central role in both fuzzy logic and neural network theory. Interpolation and learning from examples involve the construction of a model of a system from a collection of input-output pairs. In a fuzzy logic system, we assume the input-output pairs have the structure of fuzzy if-then rules that relate fuzzy variables whose values are fuzzy sets instead of numbers. Fuzzy variables facilitate interpolation by allowing an approximate match between the input and the antecedents of the rules. Generally, fuzzy systems work well when we can use experience. When we cannot do this, we use neural-fuzzy modeling to generate the rules (Kosko, 1992).

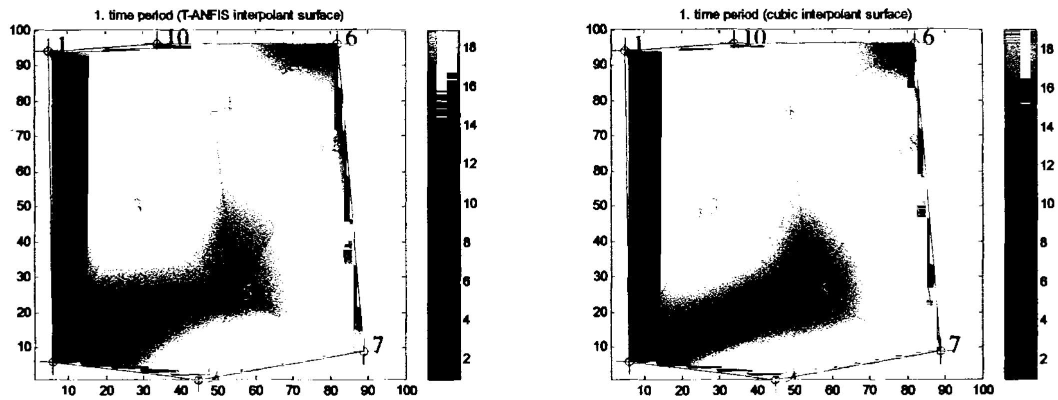
Anfis (Jang, 1993; Jang et al., 1996), a neuro-fuzzy modeling method, is also employed in the interpolation of movement data on the movement surface. Anfis, which uses fuzzy membership functions, provides a flexible structure in the interpolation process. Anfis has the advantage of learning capability. It is also a suitable method for interpolation of scattered data. Due to its hybrid structure, Anfis generates continuous movement surfaces by interpolating the number of visits (z_{t_i}). In the training of the Anfis structure, fuzzy locations and z_{t_i} values to corresponding locations are used as the input and output parameters of the Anfis respectively. For each Delaunay triangle an Anfis structure is designed using the coordinate parameters of that triangle. In the computation of the z_{t_i} value at any location within a Delaunay triangle on the $D_{(x,y,z)_{t_i}}$ surface, the trained Anfis structures serves as an interpolant. The results are then compared with the results of the traditional cubic interpolation.

Analysis of changes of visits to the locations on the $D_{(x,y,z)_{t_i}}$ surface based on time are required to obtain the spatio-temporal movement signatures of the object θ. These $D_{(x,y,z)_{t_i}}$ surfaces are computed using the Anfis and Cubic interpolation methods as can be seen in Figure 5.3. Observations are taken for 12 different time intervals in this case corresponding to months.

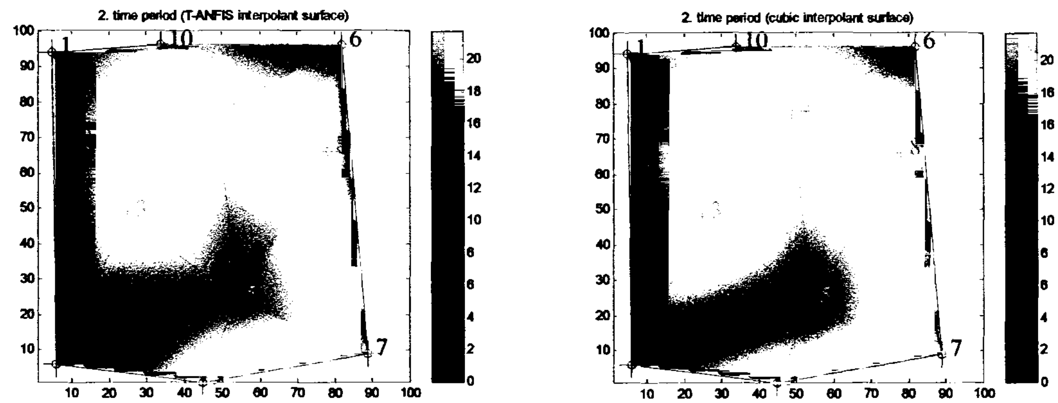
For each time interval, a $D_{(x,y,z)_{t_i}}$ surface is constructed and the shape of the $D_{(x,y,z)_{t_i}}$ surface changes based on the corresponding number of visits (z_{t_i}) to each location. The computed $D_{(x,y,z)_{t_i}}$ surfaces represent movement behavior of the object θ through out the t_i time intervals. Therefore, each of these surfaces is referred to as the "spatio-temporal movement surface" of the object θ for the corresponding t_i time interval.

Number of visits to a fuzzy location is important information in extracting the spatio-temporal signatures of moving objects. The number of visits to each fuzzy location is not known with precision, it is based on fuzzy membership assignment of number of visits to fuzzy locations. The total number of visits to each location or path over time influences the strength of hierarchy in determining the spatio-temporal location and path signatures of a moving object. Anfis supports queries on the interpolated movement surfaces to obtain specific spatio-temporal movement signatures of objects. The Figure 5.4, Figure 5.5, and Figure 5.6 show the computed spatio-temporal location signatures of the moving object for the year where z_{t_i} (number of visits) is z_{t_i}<100, 101<z_{t_i}<300, and z_{t_i}>300 respectively.

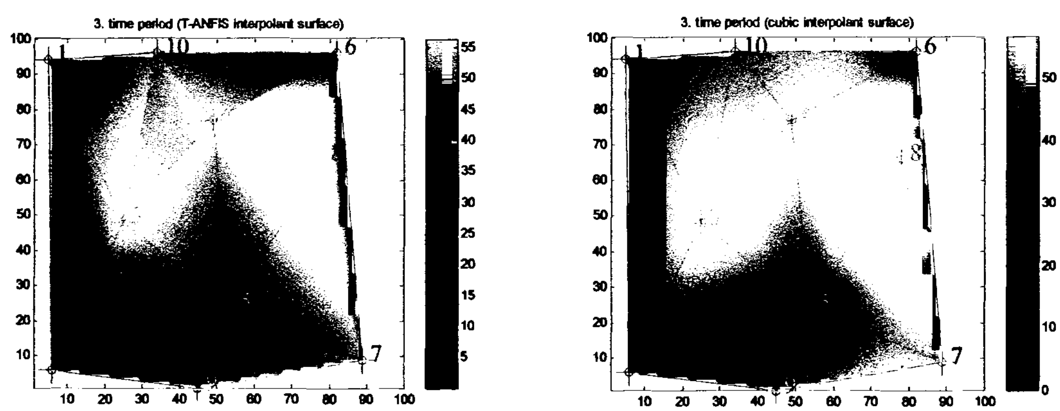
1^{st} t interval



2^{nd} t interval



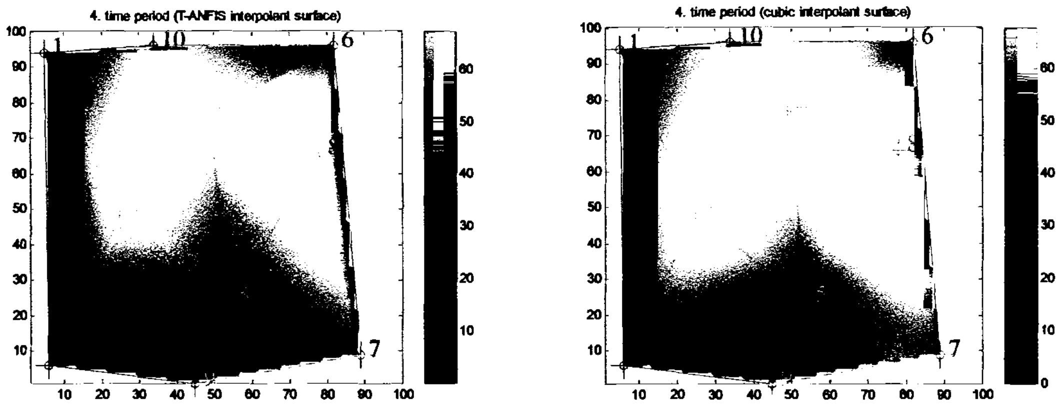
3^{rd} t interval



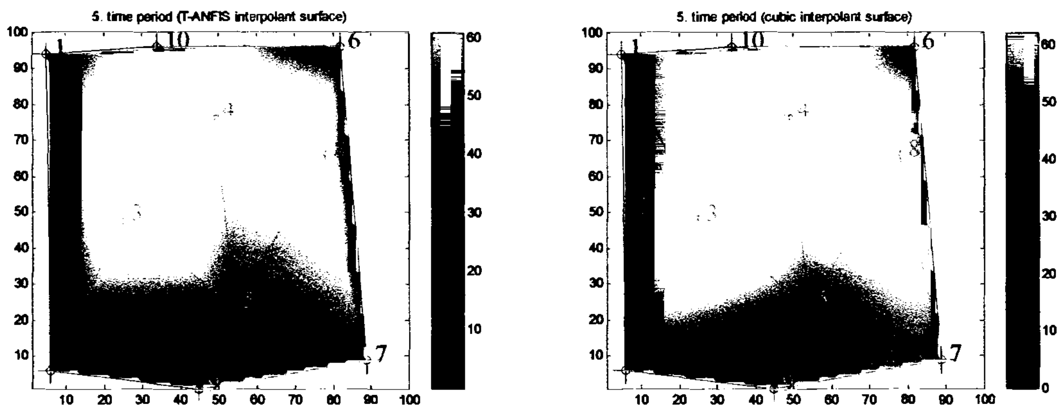
(a) (b)

Figure 5.3: Changes in the density of number of visits for each t_i computed using (a) Anfis interpolant (b) Cubic interpolant.

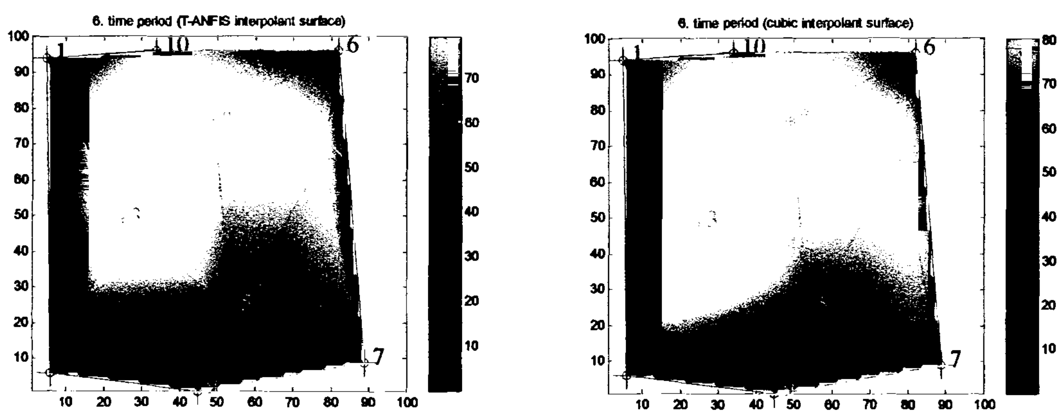
4^{th} t interval



5^{th} t interval



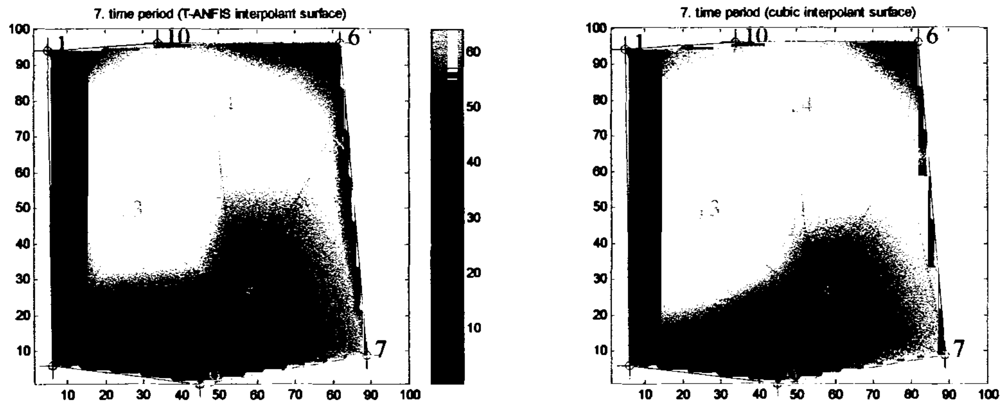
6^{th} t interval



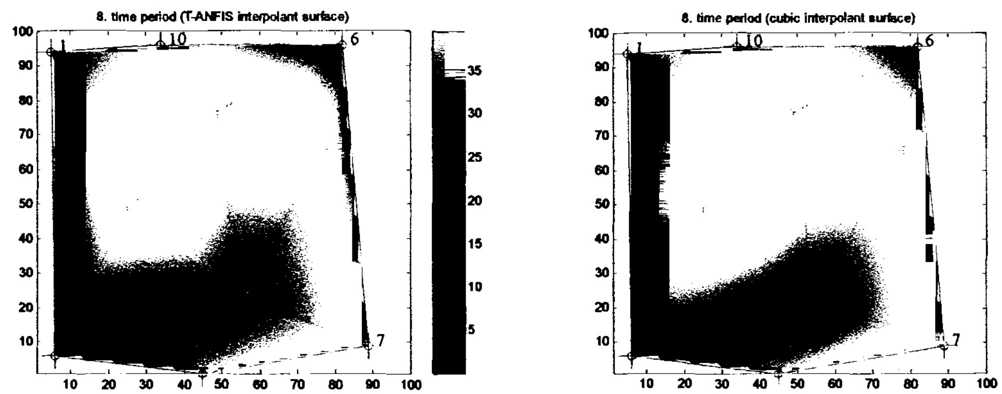
(a) (b)

Figure 5.3: Continued.

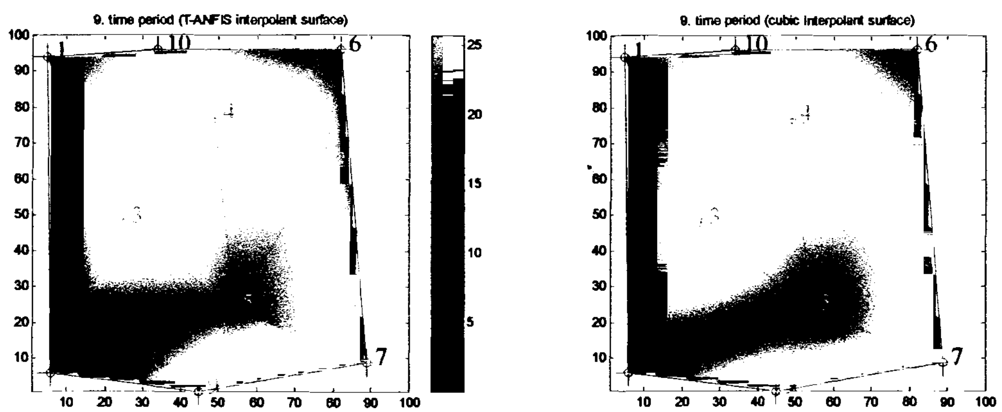
7^{th} t interval



8^{th} t interval



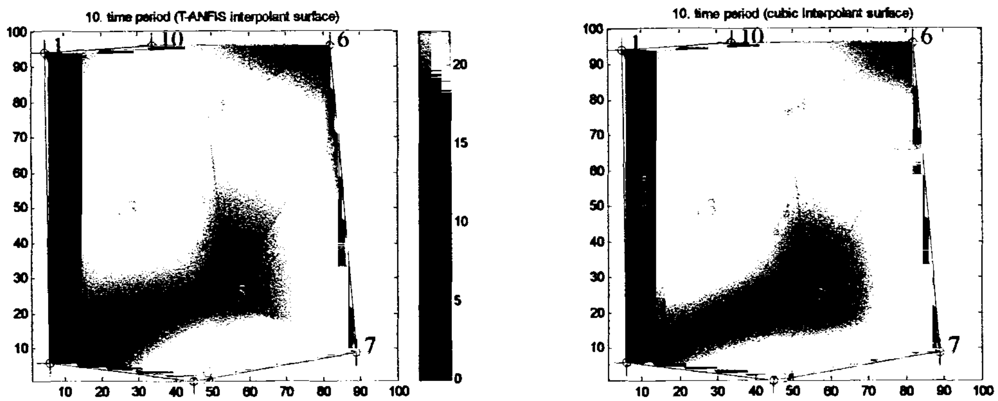
9^{th} t interval



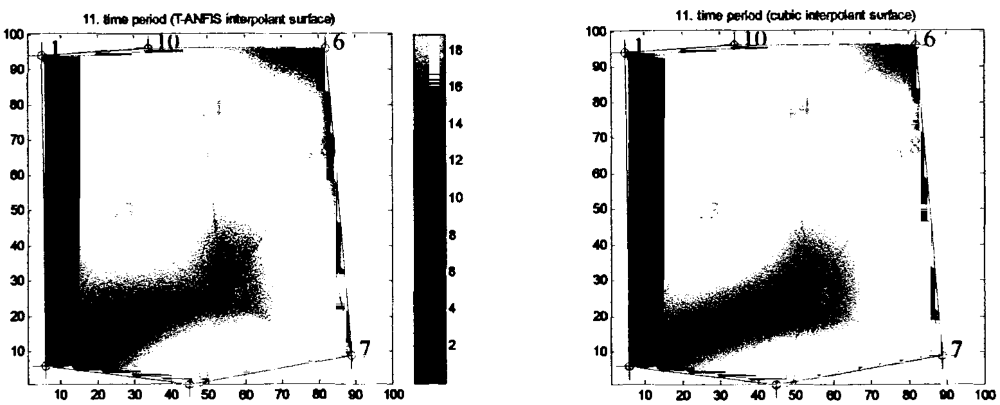
(a) (b)

Figure 5.3: Continued.

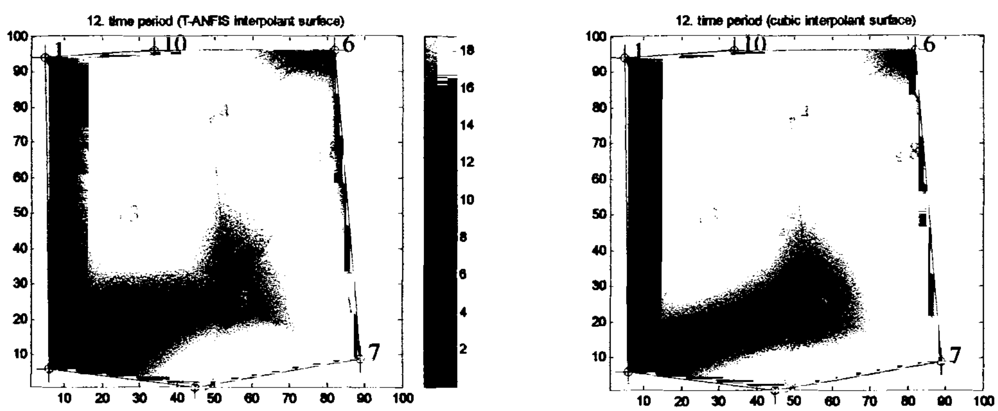
10^{th} t interval



11^{th} t interval



12^{th} t interval



(a) (b)

Figure 5.3: Continued.

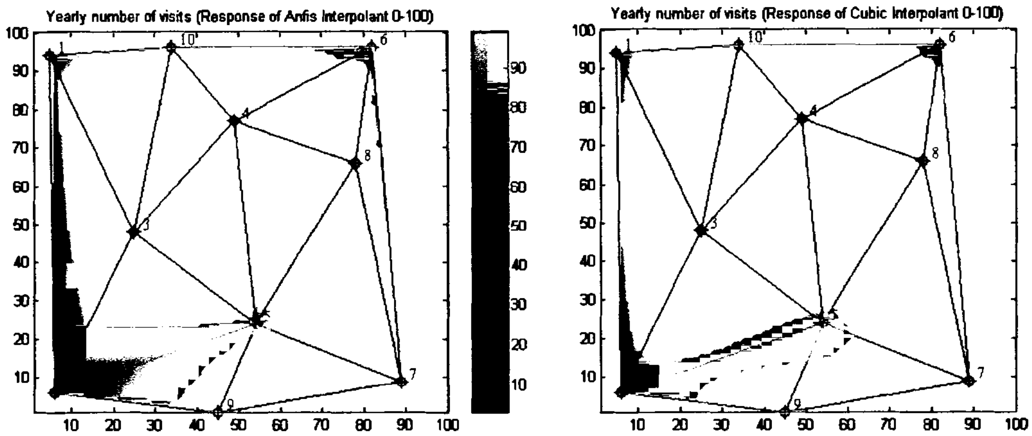


Figure 5.4: Spatio-temporal location signatures of the moving object where z_{ti}<100.

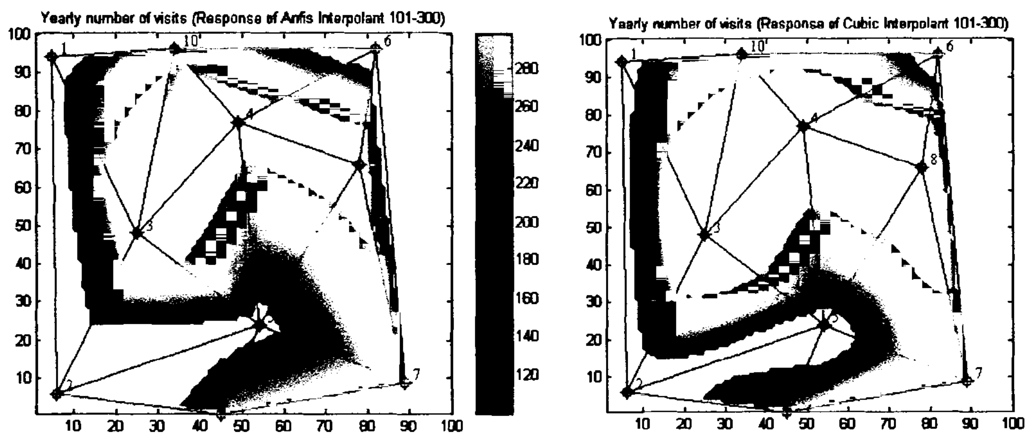


Figure 5.5: Spatio-temporal location signatures of the moving object where 101< z_{ti}<300.

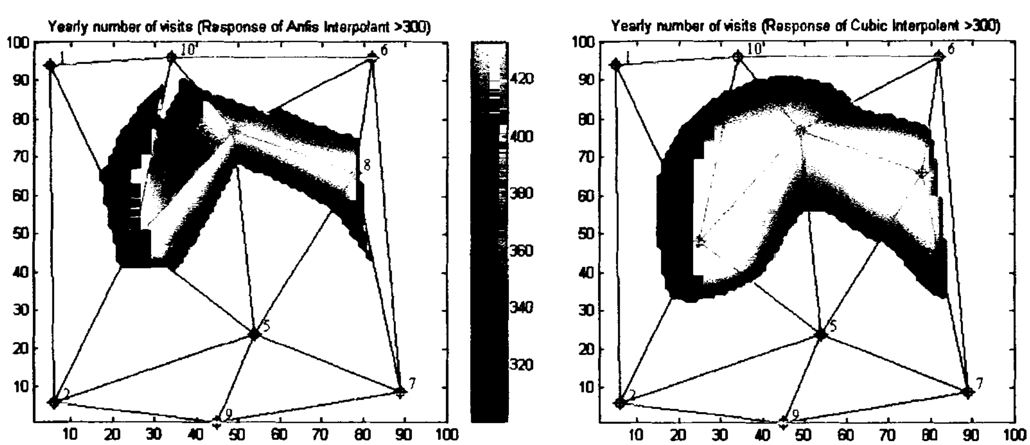


Figure 5.6: Spatio-temporal location signatures of the moving object where z_{ti}>300.

5.3.2 Movement Volume Generation and Analysis

Spatio-temporal location signatures in the form of movement surfaces as described above indicate locations where a moving object might be at a specific time point or interval. Volumes can be created and volumetric data analysis can be carried out by assembling n such surfaces for n t-intervals. In this study, the number of t-intervals (n) is chosen as n=12 corresponding to months, and V volumes are defined using these n surfaces. In this case, the object θ is described as moving in the volume V. The volume V can be computed by the t (time), x and y (location) coordinates.

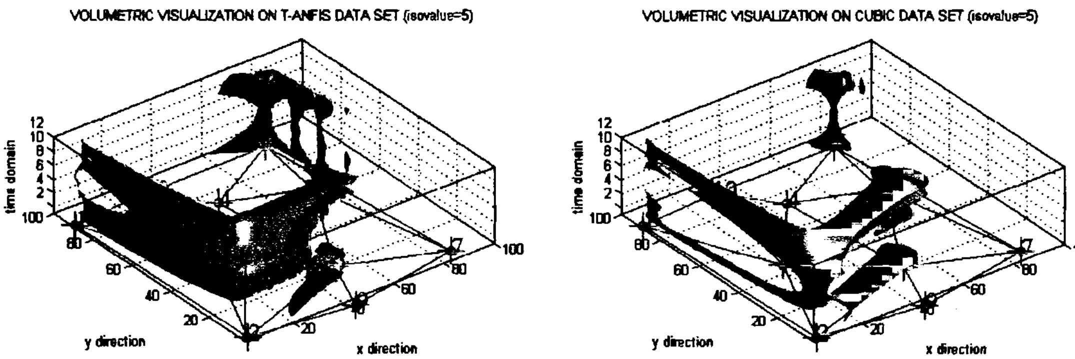
Volumetric visualization offers various advantages for data analysis such as increased understanding of complex data and easier analysis. In many of the volumetric visualization applications, iso-surfaces are computed and used for visualization purposes. It is possible to understand and interpret the specified structure in a V volume using an isovalue, represented as an iso-surface. An iso-surface is the surface that passes through all points in the volume where the scalar value is equal to a specified isovalue. An iso-surface shows a 3-D volume bounded by a particular isovalue. The iso-surface has the specified iso-level, the remainder of volume contains values greater (or less) than the isovalue. Iso-surface extraction is one of the most commonly used methods for the visualization of scalar-valued volume data.

In this thesis, the iso-surfaces computed based on the observation data represent various spatio-temporal movement signatures. For example; Figure 5.7, Figure 5.8, and Figure 5.9 illustrate three different spatio-temporal signatures corresponding to monthly movement behavior of the object.

A 2D or 3D matrix forms the basis of a surface or a volume respectively, and these are referred to as signature definition matrices. To support interpretation of these signature definition matrices, scientific visualization methods are used to isolate and highlight various isovalues and iso-surfaces. For example, isovalue = 60-70 gives us the most visited locations for any time in a year by the moving object θ. Such an extracted iso-surface is considered a specific instance of a "spatio-temporal location signature" of the object θ. In our experimental study, we have used iso-surface algorithms described in (MathWorks, 1995).

Figure 5.7, Figure 5.8, and Figure 5.9 illustrate various iso-surfaces using various iso-values and $D_{(x,y,z)_{t_i}}$ surfaces. In Figure 5.7a-b, Figure 5.8a-b, and Figure 5.9a, the extracted regions illustrate the spatio-temporal location signatures for a maximum of 5 10, and 70 visits in a year respectively.

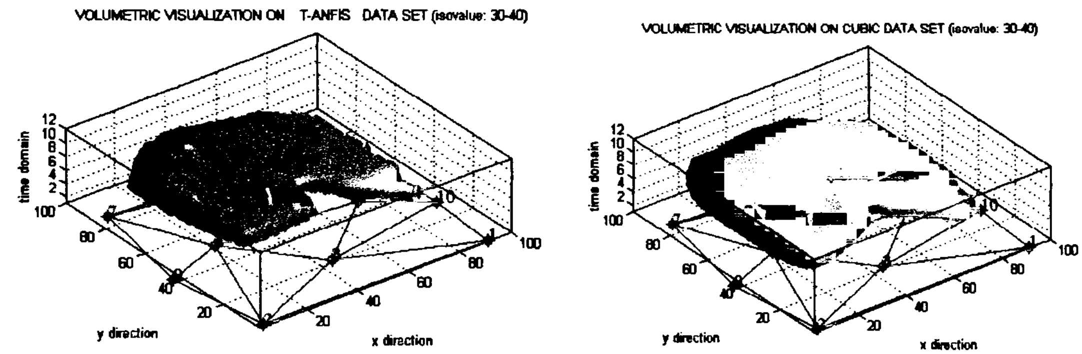
Results from the computed V volumes can be used in the analysis of movement behavior of the object θ moving on the $D_{(x,y,z)_{t_i}}$ surface through out the t domain. These movement behaviors in the form of specific iso-surfaces belonging to the object θ illustrate spatio-temporal location signatures of the object.



(a) Anfis

(b) Cubic

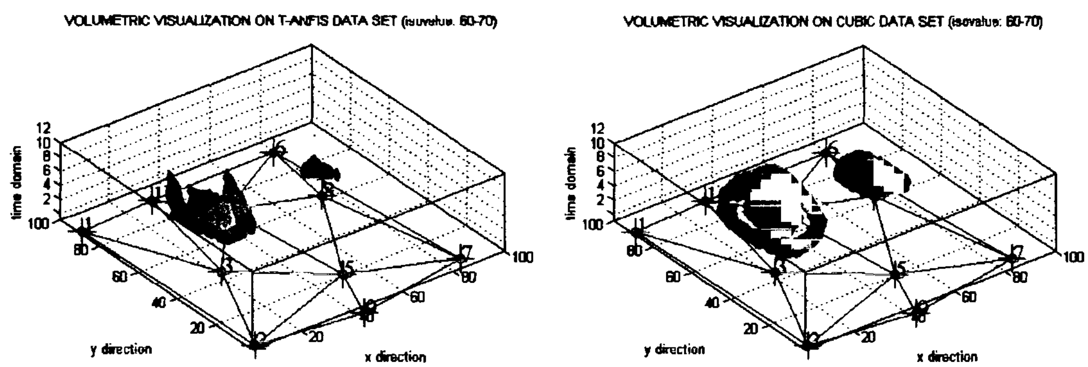
Figure 5.7: Spatio-temporal location signatures of the moving object where $z_{ti} = 5$.



(a) Anfis

(b) Cubic

Figure 5.8: Spatio-temporal location signatures of the moving object where z_{ti} = 30-40.



(a) Anfis

(b) Cubic

Figure 5.9: Spatio-temporal location signatures of the moving object where z_{ti} = 60-70.

In this thesis, Anfis and Cubic interpolant are utilized in the computations of the spatio-temporal location signatures described above. The steps listed in equation (5.2) are followed to compute the v volumes using the Anfis interpolant.

1. *Define the Delaunay triangles using the computed fuzzy locations,* 2. *Compute an Anfis for each Delaunay triangle,* 3. *Create a mesh-grid through out the x and y axises,* 4. *For each Delaunay triangle define a trained Anfis,* 5. *For each mesh grid point within a triangle interpolate* z_{ti} *values using the defined Anfis,* 6. *Choose an isovalue for volumetric visualization,* 7. *Compute the iso-surface value.*	(5-1)

In order to compare the results obtained from Anfis interpolant, the cubic interpolant is employed similarly as outlined in equation (5.3) to compute the v volumes.

1. *Define the Delaunay triangles using the computed fuzzy locations,* 2. *Compute cubic interpolant parameters for each corresponding Delaunay triangle,* 3. *Create a mesh-grid through out the x and y axises,* 4. *Determine the Delaunay triangle containing a mesh-grid,* 5. *For each mesh grid point within a triangle interpolate* z_{ti} *values using cubic interpolant.* 6. *Choose an isovalue for volumetric visualization,* 7. *Compute the iso-surface value.*	(5-2)

5.3.3 Designing a Fuzzy Reasoning Algorithm to Establish Hierarchies

A fuzzy reasoning algorithm was developed to determine a hierarchical order of the signatures embedded in the spatio-temporal signature definition matrix. The fuzzy reasoning algorithm that determines the hierarchical order consists of the following rules:

- *Rule 1*: If number of visits is NVH then order index is PO,
- *Rule 2*: If number of visits is NVM then order index is SO,
- *Rule 3*: If number of visits is NVL then order index is TO,

where NVL, NVM, and NVH denote fuzzy sets "number of visits low," "number of visits medium," and "number of visits high," respectively, and PO, SO, and TO denote fuzzy sets "primary order," "secondary order," and "tertiary order" respectively.

The membership functions of fuzzy sets NVL, NVM, and NVH for a year and for a month are shown in Figure 5.10 and Figure 5.11 respectively. Figure 5.12 shows the membership functions of fuzzy sets PO, SO, and TO.

Using the fuzzy reasoning algorithm, all z_i values corresponding to each location in the signature definition matrix are characterized by a corresponding order index value, which varies from 0 to 1. For example, the order index values of 0.9, 0.6, and 0.2 refer to PO, SO, and TO locations respectively in the signature definition matrix where z_i (see Figure 5.10) is z_{t_i}>300 (Figure 5.6), 101<z_{t_i}<300 (Figure 5.5), and z_{t_i}<100 (Figure 5.4) respectively. Similarly, the order index values of 0.85, 0.25, and 0.15 refer to PO, SO, and TO locations respectively in the signature definition matrix where z_{t_i} (see Figure 5.11) is z_{t_i}=60-70 (Figure 5.9), z_{t_i} =10 (Figure 5.8), and z_{t_i}=5 (Figure 5.7) respectively.

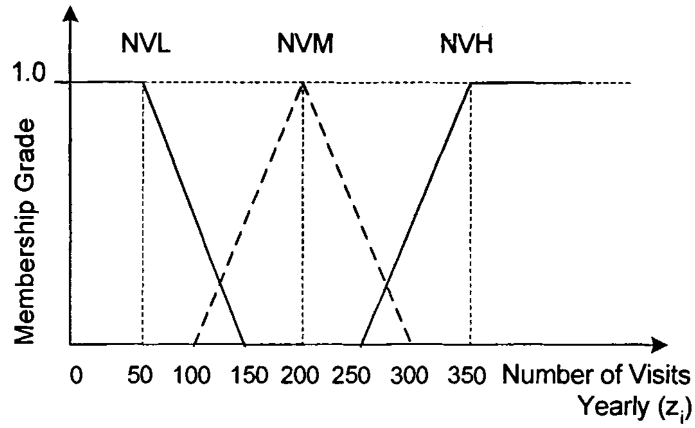


Figure 5.10: The membership functions of fuzzy sets NVL, NVM, NVH for a year.

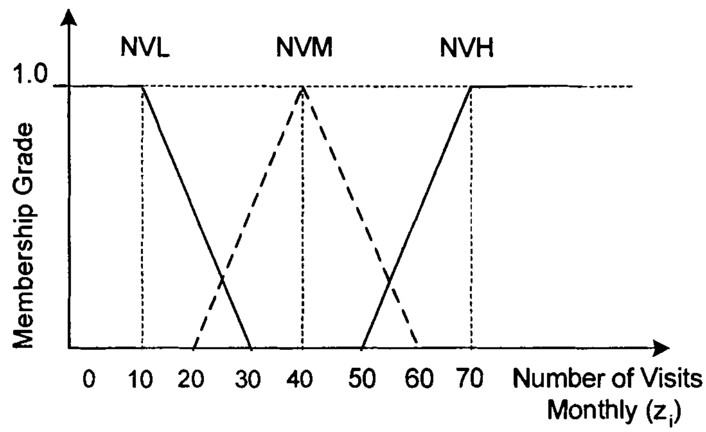


Figure 5.11: The membership functions of fuzzy sets NVL, NVM, NVH for a month.

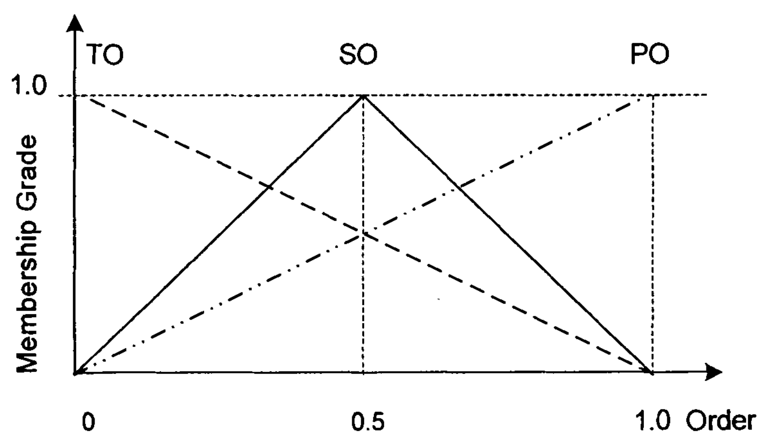


Figure 5.12: The membership functions of the fuzzy sets "PO," "SO," and "TO".

5.4 Generating Spatio-temporal Path Signatures

Other uses of the visualization tools are for analysis of changes in a specific path with time based on the number of visits. Figure 5.13 shows a potential path p through the signature definition matrix.

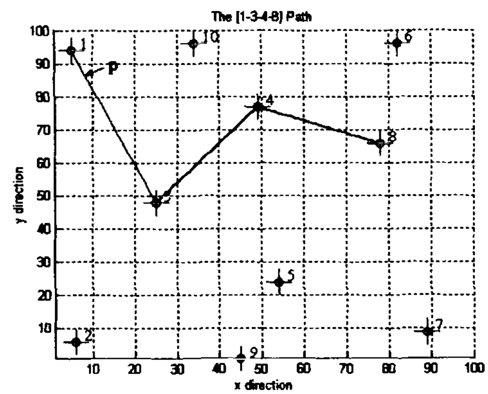
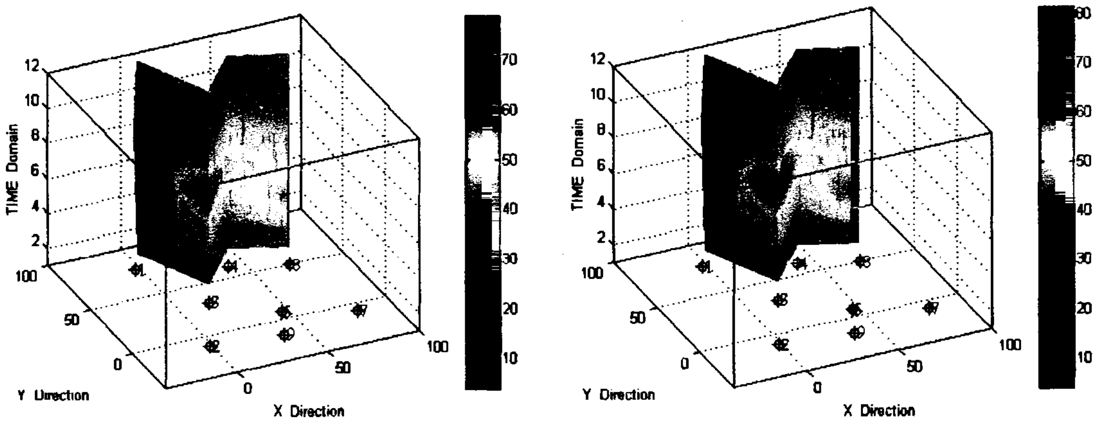


Figure 5.13: Analysis of changes of visit in a chosen path based on time.

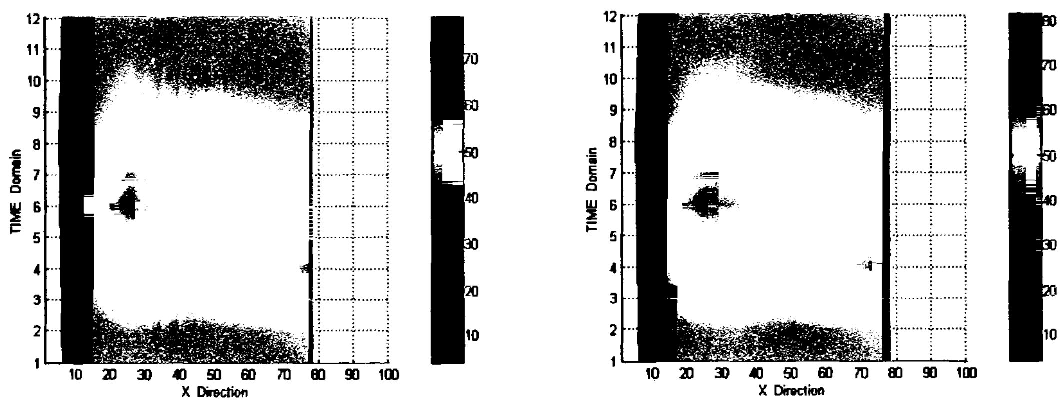
Predicted visits of the object θ along a path p based on time are visualized in Figure 5.14 and Figure 5.15 using the computed surfaces and volumes as described in sections (5.3.1.) and (5.3.2.) respectively. The computed visits based on Anfis interpolant are shown in Figure 5.14a and those based on Cubic interpolant are shown in Figure 5.14b.

The extract from the signature definition matrix for the path is a matrix that includes all the parameters created in the volume V for the t time domain. In this case, the resolution of the created path matrix will increase as the density of the coordinates defining the path increases.



(a) (b)

Figure 5.14: Changes in the density of number of visits computed using (a) Anfis interpolant (b) Cubic interpolant.



(a) (b)

Figure 5.15: Number of visits in x direction and t domain (a) Anfis interpolant (b) Cubic interpolant for path P.

5.4.1 Computing Spatio-temporal Path Signatures

Estimated number of visits are divided into five intuitive fuzzy classes using the fuzzy linguistic terms “least”, “less”, “normal”, “more”, and “most”. The method to convert the number of visits of the object θ on path p during t domain to linguistic equals using Isodata or Fuzzy c-means classifiers is given in the equation (5.4).

1. *Extract the estimated visits on path p for time t.* 2. *Assign number of visits to 5 classes using Isodata or Fuzzy C-means.* 3. *Label these obtained classes.*	(5-3)

Using the steps of (5.4), cluster centers for the corresponding five classes and their membership functions are computed. In the process of assigning a member to any class, the class with the highest membership function value or the class that has the shortest Euclidian distance to the corresponding member is chosen. The five classes and corresponding cluster centers for the numbers of visits are computed for Anfis interpolant using Isodata classification as shown in Figure 5.16a and Table 5.2a respectively. Similarly, the five classes and corresponding cluster centers for numbers of visits are computed for the Anfis interpolant using Fuzzy c-means classification as shown in Figure 5.16b and Table 5.2b respectively. The corresponding membership functions for the five classes are shown in Figure 5.17.

The five classes and corresponding cluster centers for numbers of visits are computed for Cubic interpolant using Isodata classification as shown in Figure 5.18a and Table 5.3a respectively. Similarly, the five classes and corresponding cluster centers for numbers of visits are computed for Cubic interpolant using Fuzzy c-means classification as shown in Figure 5.18b and Table 5.3b respectively. The corresponding membership functions for each five classes are shown in Figure 5.19. One can make interpretations based on the computed five classes related to the usage of the path during a year such as the path is "least" traveled in the winter months and most traveled during the summer months.

Table 5.2: The computed cluster centers for Anfis interpolant using (a) Isodata (b) FCM.

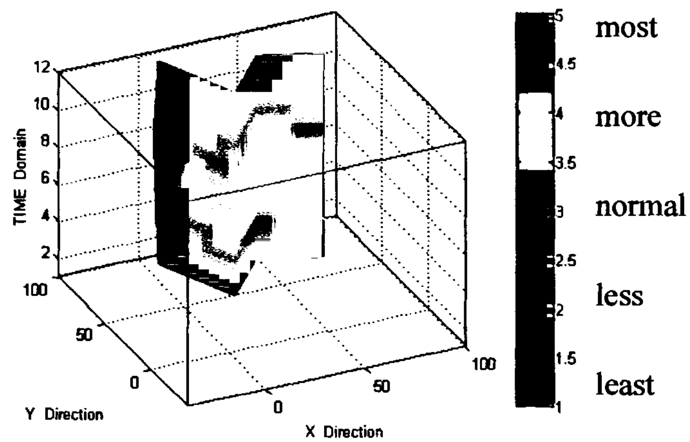
(a)

Cluster Center Numbers	Cluster Centers Anfis-Isodata
1	8.7415
2	16.158
3	26.39
4	38.389
5	55.872

(b)

Cluster Center Numbers	Cluster Centers Anfis-FCM
1	66.801
2	24.304
3	52.489
4	36.95
5	14.668

(a)



(b)

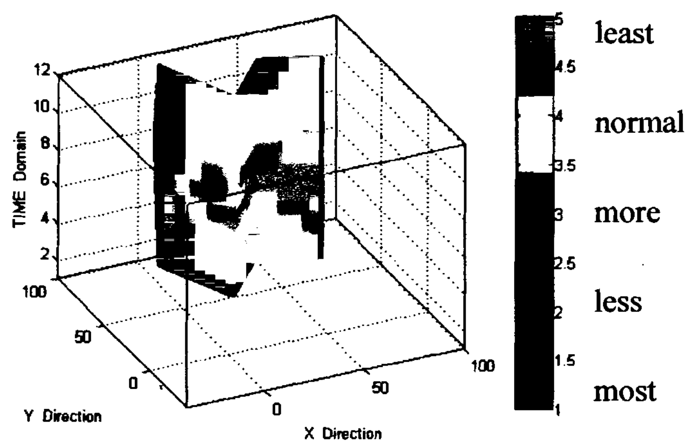
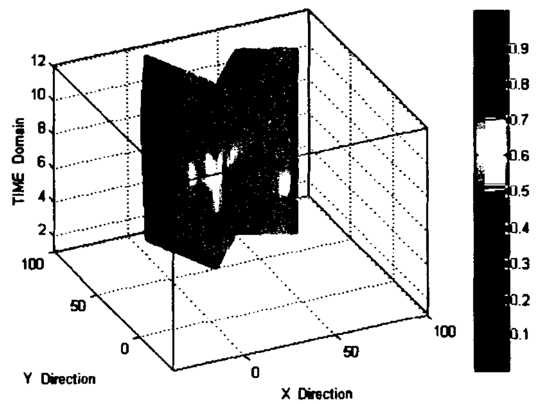
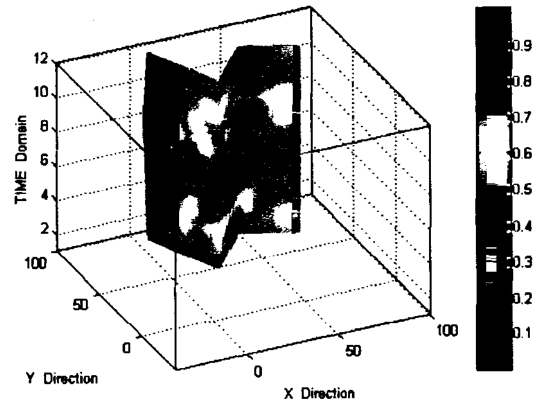


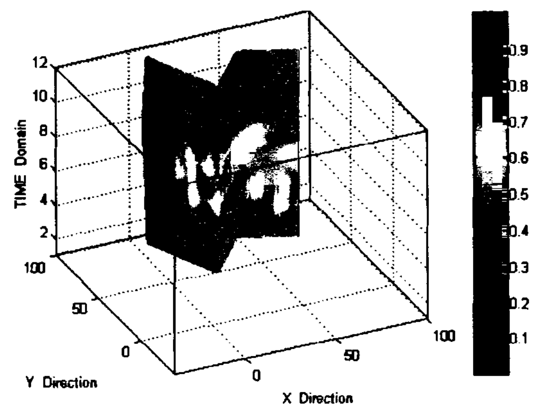
Figure 5.16: The five classes and their linguistic equals for Anfis interpolant using (a) Isodata (b) FCM.



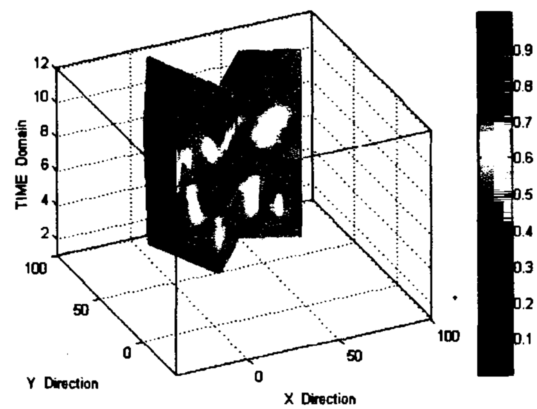
(a) MF of fuzzy class "most"



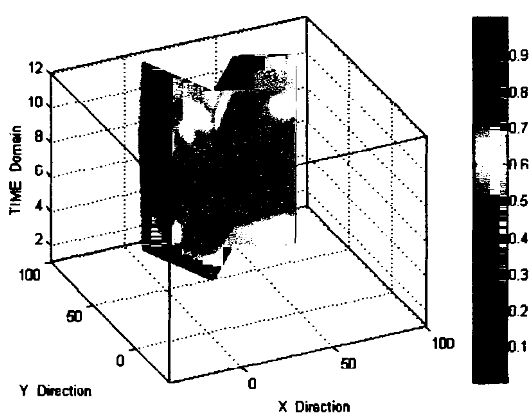
(b) MF of fuzzy class "less"



(c) MF of fuzzy class "more"



(d) MF of fuzzy class "normal"



(e) MF of fuzzy class "least"

Figure 5.17: The membership functions for each cluster for Anfis interpolant using FCM.

Table 5.3: The computed cluster centers for Cubic interpolant using (a) Isodata (b) FCM.

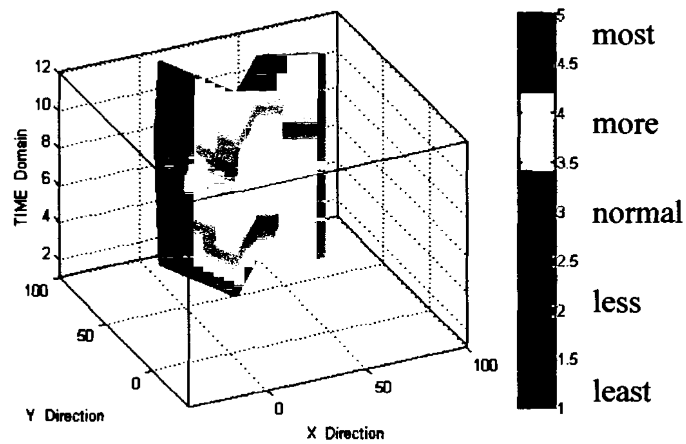
(a)

Cluster Center Numbers	Cluster Centers Cubic-Isodata
1	8.7845
2	17.043
3	28.747
4	42.388
5	60.945

(b)

Cluster Center Numbers	Cluster Centers Cubic-FCM
1	70.704
2	27.068
3	55.941
4	40.423
5	15.471

(a)



(b)

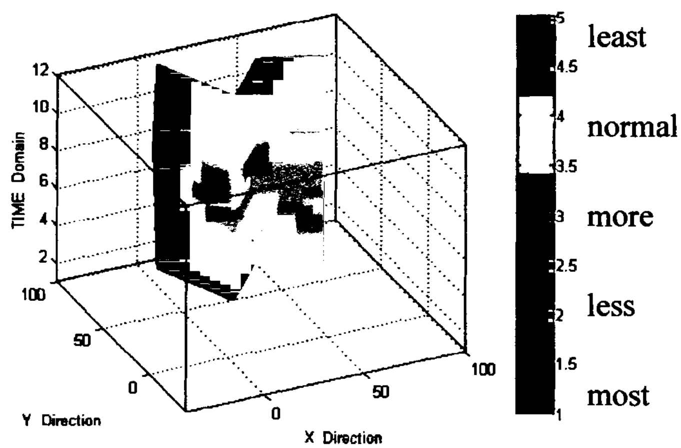
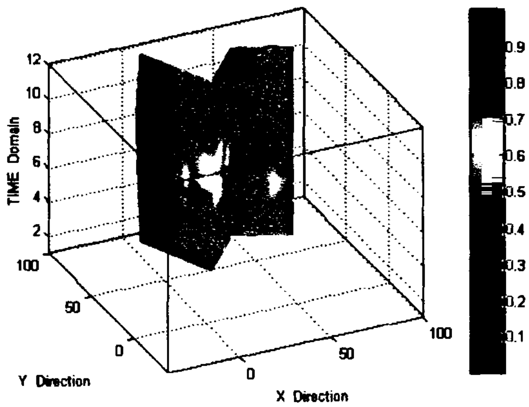
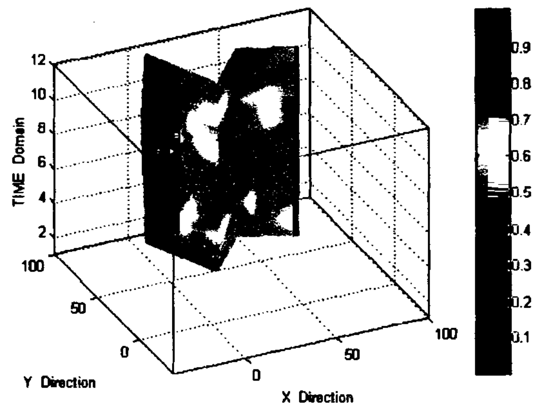


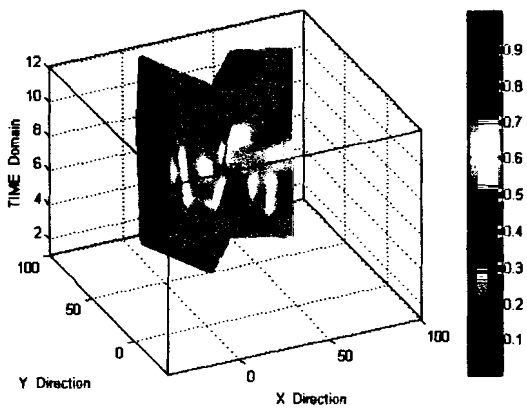
Figure 5.18: The five classes and their linguistic equals for Cubic interpolant using (a) Isodata (b) FCM.



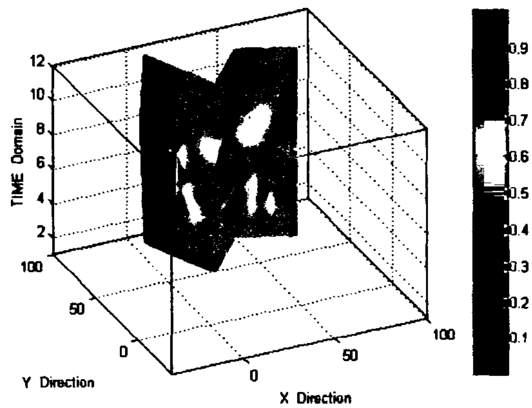
(a) MF of fuzzy class "most"



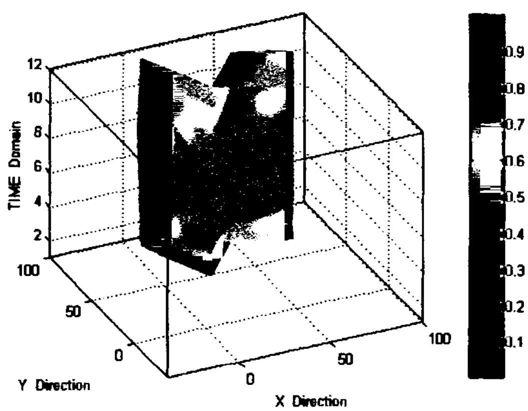
(b) MF of fuzzy class "less"



(c) MF of fuzzy class "more"



(d) MF of fuzzy class "normal"



(e) MF of fuzzy class "least"

Figure 5.19: The membership functions for each cluster for Cubic interpolant using FCM.

5.4.2 Fuzzy Rule Verification

Linguistic terms generated in previous section are used to create fuzzy rules about moving object movement behaviors. The linguistic fuzzy rules given in the equations (5.5) and (5.6) can be created by converting the results of Figure 5.16a as shown in Figure 5.20.

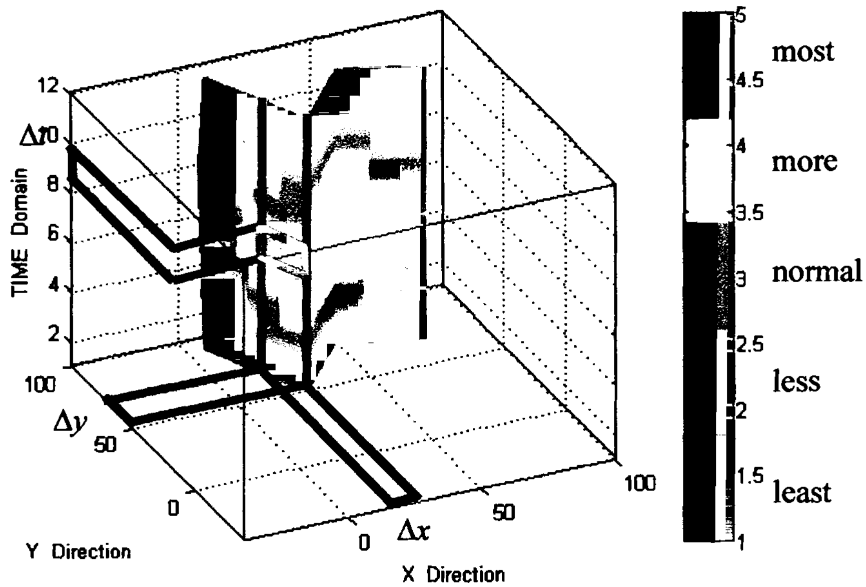


Figure 5.20: Fuzzy rule extraction/verification from Isodata classifier conversation of Anfis interpolant computations.

Fuzzy Rule #1: " For $\Delta x, \Delta y, \Delta t$ (small red rectangle referred to as "fuzzy rule polygon"), path p for the object θ in the volume V is "most" visited (Figure 5.20)." (5-4)

The truth-value of this suggested fuzzy rule may depend on the observations and the interpolation algorithm employed. The weight of this fuzzy rule can be accepted as 1 or close to 1. If the fuzzy rule does not depend on the observations, the truth-value of this fuzzy rule can be controlled easily based on observations in the volume v.

Fuzzy Rule #2:"For $\Delta x, \Delta y, \Delta t$ (fuzzy rule polygon), path p for the object θ in the volume V is "least" visited (Figure 5.20)." (5-5)

The truth-value of this suggested fuzzy rule can be controlled easily based on observations in the volume v. In this case, it is clear that the truth-value of this suggested fuzzy rule is small. Therefore, the weight of this fuzzy rule can be expressed as 0 or close to 0. In choosing the optimum weights, the suggested fuzzy rule polygon formed by intersection of $\Delta x, \Delta y$ and Δt can be compared with the fuzzy rule polygon (linguistic class "most") computed based on observation data using the above-mentioned various mathematical approaches of the volume V and its interpretations. The degree of the agreement between fuzzy rule #1 and fuzzy rule obtained based on observation can be compared as a fuzzy rule truth-value weight.

Chapter 6

CONCLUSIONS

This thesis concentrated on modeling movements of objects in spatial and spatio-temporal extents through movement signatures. Spatial signatures, which include dominant or frequently visited locations and paths, and spatio-temporal signatures, which associate a temporal pattern with the spatial signatures, of a moving object were identified and extracted from large volumes of data.

In this thesis, fuzzy and neuro-fuzzy methodologies were implemented in the extraction of movement signatures. The proposed methodologies are a step to incorporate the similar modeling methodologies that are used by humans into information systems. Identification of movement signatures and definition of their attributes provides summary level information for modeling and reasoning about moving objects. This chapter, summarizes the thesis (Section 6.1), describes results and major findings (Section 6.2), and highlights future work made possible by this research (Section 6.3).

6.1 Summary of the Thesis

In this thesis, we introduced the use of fuzzy and neuro-fuzzy methodologies for modeling movements of objects based on the properties and the patterns they exhibit in the real world. We specified the basics for building fuzzy and neuro fuzzy models for the representation of moving objects. General knowledge about patterns of moving objects can be acquired by analyzing a set of movement observations. Because it is not possible to store exact knowledge about the movement of objects and their environment, we proposed to use movement signatures of objects and the approximate knowledge related

to them to cope with related estimations such as the possible locations and approximate paths of a moving object. Methods to extract movement signatures from a set of movement observations were developed. We also discussed certain aspects of the implementation of the fuzzy and neuro-fuzzy models to obtain movement signatures.

Chapter 4 demonstrated an approach to derive spatial location signatures of an object from a set of position observations with no time information given. The fuzzy c-means clustering was employed over the observations. By clustering the observed positions of a moving object, a set of fuzzy locations frequently visited by the object was identified. The fuzzy membership functions related to the fuzzy locations were developed. Each fuzzy location consists of a set of positions and their degree of membership to the location.

Chapter 5 described an approach to extract spatio-temporal movement signatures of the moving object using the fuzzy locations obtained as explained in Chapter 4. Two additional movement parameters namely number of visits (z_i) and the time of the visits (t_i) to each fuzzy location are provided and used in the computation process of obtaining spatio-temporal movement signatures of an object. Number of visits to a location is important information in extracting spatio-temporal signatures of moving objects. The total number of visits to each location or path over time is used as the basic parameter that influences the strength of hierarchy in determining the spatio-temporal location and path signatures of a moving object.

In the proposed approach, spatio-temporal movement signatures of the object are extracted from surfaces or volumes described by a signature definition matrix. A series of methods including conventional, fuzzy, and neuro-fuzzy methods were used to generate

signature definition matrices. Anfis interpolant the neuro-fuzzy method used to generate signature definition matrices. Queries to these matrices are used to obtain the spatio-temporal movement signatures of objects. The Figure 5.4, Figure 5.5, and Figure 5.6 show extracts of the spatio-temporal signature matrix of a moving object for the year where z_i (number of visits) is z_i<100, 101<z_i<300, and z_i>300 respectively. A Cubic interpolation method was similarly applied to generate the spatio-temporal signature definition matrix. The results indicate that the Anfis interpolant as an alternative approach gives comparable results to the Cubic interpolant.

A fuzzy reasoning algorithm was developed to determine a hierarchical structure for the signatures embedded in the spatio-temporal signature definition matrices. Using the fuzzy reasoning algorithm, all z_i values corresponding to the each location in the signature definition matrix are characterized by a corresponding order index value, which varies from 0 to 1 (see section 5.3.3).

6.2 Contributions

The major contributions of this thesis can be outlined as follows:

- The concept of "movement signatures" is introduced.

  The concept of "movement signatures" is introduced as a concept that can be used in modeling moving objects. This new model makes more effective use of movement observations, and imprecise and uncertain information related to movements of objects in obtaining meaningful movement patterns. The proposed methods to identify and formalize elements of movement signatures for individual objects are the main contribution of this thesis.

- An approach to define and extract movement signatures is demonstrated.

  Movement patterns of an object are summarized in the form of movement signatures in both spatially and temporally. Defining and extracting movement signatures from a set of observations are demonstrated.

- Fuzzy and neuro-fuzzy methods are implemented with success in extracting movement signatures.

  The implementation of fuzzy and neuro-fuzzy methods in modeling movements is another major contribution of this thesis. The proposed methods support queries regarding the movements of objects and provide higher-level structures for subsequent analysis and reasoning about movements.

The hypothesis of this thesis was:

"A set of position observations on a moving object reveal high-level movement patterns over space and time."

The following findings of this thesis support the hypothesis:

- Large numbers of unstructured observations were transformed by cluster analysis to fuzzy locations that define location signatures.
- Aggregated observations now associated with location signature were summarized as number of visits providing the basis to establish hierarchical order among location signatures.
- Ordered location signatures could then be connected to identify path signatures (higher-level concept that does not indicate specific path but connections between frequently visited locations).

Results demonstrated the validity of the hypothesis by highlighting:

- Explanations on movements of an object require the description of its movement patterns.
- A moving object exhibits a wide range of movement patterns over space and time.
- Movement patterns can be acquired by analyzing a set of movement observations.
- Movement patterns extracted from a set of observations improve modeling and reasoning about unobserved movements of an object.

6.3 Future Research

This thesis presents new methods of modeling moving objects and handles related uncertainties, but the full utility of these methods remains for further investigation. Although this thesis has demonstrated significant results in the field of movement modeling by the development of novel models and methodologies, this research also discovered new issues and problems that need further research.

6.3.1 Using Signatures for Prediction Purposes

The components of the proposed model of this thesis: observations, profiles, and movement signatures provide a foundation for making estimations and predictions related to the movement of objects. The addition of movement signatures will enhance the ability to more reliably estimate moving object positions and paths. The development of estimation and prediction methods needs to be considered in future research.

Designing summary operations over movements of objects is area of ongoing research. Additional methods for summarizing movements of objects need to be identified. We are interested in further summarization methods using fuzzy and neuro-fuzzy methodologies.

One area of particular interest is to more formally investigate the uncertainties associated with the estimation of positions and paths of a moving object. The computation of either a location or an expected path cannot be exact and thus the reported result and presentation should provide some indication of the degree of uncertainty.

The selection of different membership functions leads to differences in the accuracy of the obtained results. Therefore different scenarios containing different sets of fuzzy membership functions need to be analyzed for refining the characterization of signatures. Therefore, there is a need to develop methods to further evaluate designed fuzzy models and membership functions.

6.3.2 Reasoning

Boolean logic based models of reasoning have the attractiveness of completeness and mathematical rigor, but often they have limited applicability to the imprecise situations of real life (Gaines, 1976). They conventionally attempt to be precise and refuse the fuzziness and imprecision of concepts in real life and replace them with precise simplifications (Dutta, 1990). Zadeh (Zadeh, 1975) suggested that the essence and the power of human reasoning lie in the ability to grasp and use inexact concepts directly. He further argues that efforts to model human reasoning processes via formal systems of increasing precision shall lead to decreasing validity and relevance (Zadeh, 1979).

Zadeh (Zadeh, 1974) formally used the term approximate (fuzzy) reasoning to describe much of human reasoning. He (Zadeh, 1979) defined approximate reasoning or equivalently fuzzy reasoning as the process or processes by which an imprecise conclusion is deduced from a collection of imprecise premises. Fuzzy reasoning is appropriate to solve a variety of problems in the real world. As mentioned before, much

of human reasoning is approximate and imprecise but produces relevant outcomes. Humans often convert precise quantitative information into qualitative values (or categories) to gain insight into the true meaning of the data (Booth, 1989). Consider for example, the case of walking through a building. We may only approximate distances and locations to various objects (humans, tables, doors), however we nevertheless manage to find our way easily many times in a day. One can think of many other real world examples including parking a car, moving between home and work locations, playing soccer, and landing an airplane. There are many other real world scenarios where various factors encourage the use of fuzzy reasoning methods for moving objects. One should keep in mind that no standard method exists for transforming human knowledge or experience into the rule base and database of a fuzzy inference system. In addition, there is need for effective methods for tuning the membership functions (MFs) so to as minimize the output error measure or maximize performance index.

In many instances, reasoning about moving objects is based on the concept of similarity. Fuzzy and neuro-fuzzy methods are well suited for modeling, reasoning, and similarity analysis purposes since geographic phenomena are not always well defined with crisp boundaries (Yuan, 1997). Fuzzy and neuro-fuzzy modeling and reasoning methodologies have started to be implemented in various GIS and remote sensing applications such as change detection, classification of geographical data, improving image analysis, and analyzing uncertainty (Dragicevic and Marceau, 1999; Papadias et al., 1999; Stefanakis et al., 1999). Future research should include developing methodologies to reason about spatio-temporal information expressed in the form of linguistic descriptions, similar to the kind of information processed by humans.

6.3.3 Dynamic Fuzzy Sets

The concept of dynamic fuzzy sets for which membership values are allowed to change is introduced (Kosanovic, 1995). The concept of a dynamic fuzzy set (Buller, 2001) is a way of fuzzy inferencing that allows for the resulting judgment to change with time. The method of judgment generation employs the concept of fuzzy set and adds a temporal aspect to the classic fuzzy logic. The concept of dynamic membership functions offers new ways of understanding and modeling movements of objects.

6.3.4 Fuzzy Cartesian Coordinate System

In many moving object applications the objective is to deal with modeling problems in environments that are uncertain, unpredictable, and possibly unstructured and dynamic. Modeling movements of objects in such real world environments requires access to information about locations of obstructions and/or landmarks. This type of spatial information is typically represented in the form of a map. Traditional approaches to map representation have attempted to capture explicit metric information about the environment. However, as an alternative, a map representation based on fuzzy relations is proposed in (Tunstel, 1995) that can be used to model movements of objects as shown in Figure 6.1.

In this proposed approach, spatial information can be represented in a map that reveals an approximate distribution of objects in some region of interest. The uncertainty of this distribution is represented as a fuzzy relation, which can be thought of in this case as a "Fuzzy Cartesian Coordinate System" where coordinates are approximate locations of objects in the map (Tunstel, 1995). In the Figure 6.1, two-dimensional "Fuzzy Cartesian Coordinate Systems" can be seen.

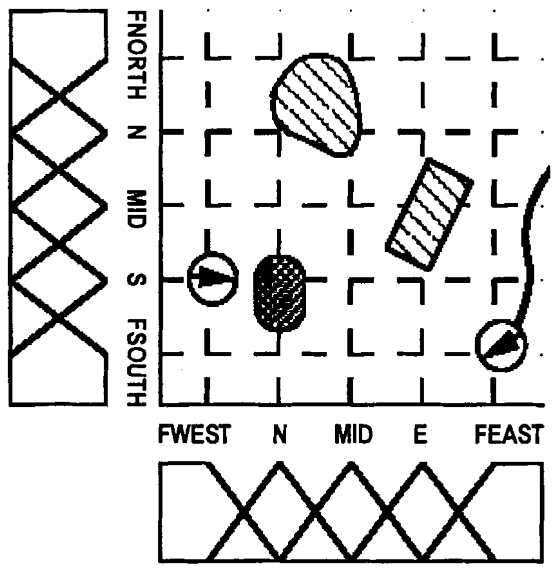


Figure 6.1: Fuzzy Cartesian coordinate system.

This proposed approach offers ways of modeling movements of objects and related uncertainties. The two-dimensional "Fuzzy Cartesian Coordinate System", which represents locations of objects and obstructions using the fuzzy direction membership functions such as FNorth and FWest as shown in Figure 6.1 could be used to create the fuzzy rules base. This provides an approximate representation of the movements of objects. The use of the "Fuzzy Cartesian Coordinate System" to model movements should be further investigated.

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APPENDIX

DELAUNAY TRIANGULATION

A triangulation is a subdivision of an area (volume) into triangles (tetrahedrons). The Delaunay triangulation is the dual structure of the Voronoi diagram. A Voronoi diagram is the partitioning of the plane into polygonal regions where each region is the set of points in the plane that are closer to some input point than to any other input point. Voronoi diagrams were first discussed by Peter Lejeune-Dirichlet in 1850. However, the first paper about Voronoi diagrams was written by Voronoi in 1908. If the Voronoi diagram is computed using cluster centers, neighborhood borders of a surface can be obtained.

Delaunay triangulation named for the Russian mathematician, Boris Delaunay is among the most popular techniques used for generation of surfaces. Delaunay triangulation (Aurenhammer, 1991; Gold, 1979) is a triangulation of a set of points with the condition that no point in the point set falls in the circumcircle of any triangle in the triangulation. There are two stages in the Delaunay triangulation method: placement of the surface vertices and triangulation. There are several Delaunay triangulation methods (Lee and Schacter, 1980; Owen, 1998). One of the methods used in Delaunay triangulation consists of inserting a point to the triangulation shown in Figure A.1a, finding all existing triangles whose circumcircle contains the new point and deleting them, which creates a convex cavity as shown in Figure A.1b. The final version in which the new point is inserted and connected to all the vertices on the boundary of the cavity is shown in Figure A.1c.

(a) (b) (c)

Figure A.1: Delaunay triangulation over the author face.

In the context of this thesis triangulation, is used for surface construction of the movement behaviors of objects described further in chapter 4. The perception of changes in the observed movement parameters is facilitated with a data visualization approach. In (Walsum et al., 1996) the objective of visualization is stated as "the extraction of meaningful features from large data sets" where one of the feature sets of interest might be surface connectivity. Examples of such considerations consistent with the problem of this research are summarizing the data points into meaningful groups and examining regions of interest by data reduction and compaction.

BIOGRAPHY OF THE AUTHOR

H. Mustafa Palancıoğlu was born in Kayseri, Turkey in 1970. He received his Bachelor of Engineering (Surveying Engineering) degree from The Yıldız Technical University, Istanbul, Turkey in 1992. He then joined the Department of Civil Engineering, Erciyes University, Kayseri in 1993 where he worked as a research associate. He received his Master of Engineering degree in 1995 from The Yıldız Technical University, Istanbul, Turkey. He is a member of the Surveying Engineers Association of Turkey.

He enrolled for graduate studies in Spatial Information Science and Engineering at the University of Maine in the fall of 1997, and then joined the National Center for Geographic Information and Analysis (NCGIA) in 1998 and worked as a research assistant until 2001. H. Mustafa is married and has two sons.

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