DISCERNIBLE SPATIAL CONFIGURATIONS IN BUILT AND TRANSIENT SCENES

by

Georgios Panteras
A Dissertation
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DEDICATION

I would like to dedicate this Doctoral dissertation to my beloved family – my father Dimitrios, my mother Despoina and my sister Michaela for their unconditional love and support throughout my entire life. The values and the ideals they have instilled in me will forever define my personality and motivation in my endeavors.

Also I would like to dedicate this effort to my dear Christina for walking next to me in this path by illuminating each of my steps with her optimism and for her absolute faith in me.

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LIST OF ACRONYMS

9IM	9 Intersection Model
AI	Artificial Intelligence
AOV	Angle of View
API	Application Programing Interface
CV	Computer Vision
DE - 9IM	Dimensionally Extended 9 Intersection Model
DEM	Digital Elevation Model
Exif	Exchangeable Image File
GIR	Geographic Information Retrieval
GIS	Geographic Information System
GIScience	Geographic Information Science
GSD	Ground Sample Distance
HoF	Histogram of Forces
IR	Information Retrieval
JEPD	Jointly Exhaustive and Pairwise Disjoint
KDE	Kernel Density Estimation
NBTree	Naive Bayes/Decision-Tree Hybrid
NCC	Normalized Cross Correlation
NED	National Elevation Data
$OPRA_m$	Oriented Point Algebra
QSR	Qualitative Spatial Representation and Reasoning
RCC	Region Connection Calculus
RS	Remote Sensing
TPCC	Ternary Point Configuration Calculus
VGI	Volunteered Geographic Information

ABSTRACT

DISCERNIBLE SPATIAL CONFIGURATIONS IN BUILT AND TRANSIENT SCENES

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This dissertation addresses the development of metrics for scene similarity assessment using abstract spatial relations among objects comprising of a scene. This is done in the context of an ontological approach as it can support scene matching and ontology classification. We consider that abstract spatial relations are more important than absolute and/or quantitative spatial relationships in deriving semantic features for an ontology driven scene similarity. The motivation of this study arises from the semantic gap that currently exists in the majority of scene modeling methods and the insufficiency on describing higher-level knowledge representation that applies in a specific spatial context. Therefore there is currently a need to develop novel metrics to successfully describe the abstract spatial context of complex features and better communicate this information in the context of ontologies. Our approach is based on the creation of spatial signatures for complex features as they express the spatial relations of their components.

These relationships, which can be articulated through an extension of fuzzy Allen relationship, can then be quantified through the Histogram of Forces approach. Once such expressions are derived two or more scenes can be compared through the correlation analysis. Borrowing from data mining principles, the process can become computationally more effective by analyzing variations in the multiple relations that exist among various components. The proposed framework is applied in two representative test cases that express established and emerging geospatial analysis challenges. The first test case addresses structured built environments in satellite imagery, using airport compounds. The second test case addresses unstructured environments in crowdsourced data, using social media contribution patterns in the aftermath of natural disasters.

CHAPTER 1: INTRODUCTION

1.1 Problem Statement

This dissertation addresses the problem of comparing scenes of objects, in order to find similarities among them. Accordingly, we argue that a scene is a composite structure, comprising individual components (e.g. objects) as they are arranged in space. In the context of this dissertation we consider in particular the topological and directional relations among such objects (rather than solely their distances), as they tend to be more robust to the various constraints imposed upon such scenes by the sociocultural and topographical particularities of places all over the world. For example, an airport has to have certain components in order for it to fulfill its function, and these components have to have a specific spatial arrangement as well. However, their particular geometric properties may vary: e.g. in the case of an airport, the length of the runway or the size and shape of a terminal vary widely among various airports, but these two entities always have to be adjacent to each other in order for them to fulfill their function. This dissertation addresses the development of an approach to compare scenes based on the arrangement of objects within them, and the use of this capability to label scene content.

In order to achieve that, we developed a framework that performs scene similarity assessment using abstract spatial relations among the objects comprising a scene. In it, abstract spatial relations are quantified and compared among object pairs, and a scene is defined as the aggregate of these pairwise relations across all objects defining the scene. This builds upon earlier work in the computer vision and artificial intelligence communities, more specifically on Histograms of Forces and fuzzy Allen relations to detect and codify relationships among objects. This developed framework will be applied to two different test cases, in terms of data types that comprise a scene. In the first test case we have developed a scene similarity framework that builds upon these solutions to develop a scene comparison framework, and we demonstrate its performance in built environments. More specifically, we have applied our approach to a dataset of various types of airports, and demonstrated its capability to label/classify incoming datasets to one of three types (civilian, military, or joint). One could consider this to be the equivalent of introducing ontologically-derived scene arrangement metrics into the scene interpretation process. Nevertheless, the focus of the work is not on the ontology part, but rather on the comparison. The challenge when considering this type of applications is to design a methodology that will avoid the limitations of a rigid quantitative scene matching based solely on metric information, which as it is explained in the following chapter was a limiting factor for the challenging task of scene similarity so far.

In the second test case of this research we investigate the potential use of this approach in more abstract scenes. As an example we will apply the concept of a scene to the clusters of individuals reporting natural events (using wildfires as a representative example). This conceptual scene will be defined through the relations among clusters of reports and the location of the actual event, and we will investigate whether our technique will allow us to detect discernible patterns in such situations. The challenge when considering this type of applications is that we do not know whether these scenes actually do have discernible spatial patterns associated with them. Whereas in an airport form follows function, and this leads to topologically consistent arrangements, nobody knows whether responses to an event actually follow any such reason.

1.2 Motivation

Nowadays the growing size of geospatial databases has led to a point where the complexity of accessing and retrieving relevant knowledge has increased significantly. NASA, for example, generates about 5 TB of data per day indicating that an increase in volume, velocity, and variety of data products is a fact which arise the issue of the so called ‘Big Data.’ These vast amounts of data create new challenges in assessing the information accurately and timely from the geospatial databases. It becomes apparent that now more than ever it is necessary to develop geospatial computing techniques that will facilitate fast knowledge discovery and decision making that overcome the limitations of the existing purely quantitative measures. Therefore, an integrated framework to perform scene-matching using abstract metrics (e.g. topology) and assess its value for geospatial information retrieval consists of a challenging task. Geospatial and/or geographic information retrieval (GIR) (see Jones and Purve, 2009), a sub-field of Information Retrieval (IR) with the addition of spatial and geographical oriented indexing and retrieval, provides us with a strong tool to tackle these new challenges and successfully manage large-scale geospatial databases. In order GIR to be meaningful it needs to minimize the semantic gap between analysts' models of visual patterns and computers' representation of information, so as to enable users to easily access databases using query methods similar to the analysts' reasoning (Barb and Shyu, 2010). These semantics are not captured in the traditional pixel- and object-based classification schemes or by the use of low-level image features (such as, color, texture, size, and shape) since higher level descriptors and important spatial (topological) relationships can lead us to higher level semantic concepts (Vatsavai et al., 2012).

Spatial scene similarity primarily compares objects that comprise a scene based on their spatial relations across different databases for various purposes. It is perceived as a function of correspondence of objects, their spatial relations, or both, across spatial scenes or databases (Frontiera *et al*., 2008). This type of similarity between objects is examined in terms of best matching among their geometric approximations, for instance the minimum bounding rectangles (Papadias *et al*., 1995), and the sketched outlines (Stefanidis *et al*., 2002). Similarity based on the spatial relations is mainly focused on the matching of their geometric representations based on the individual relation of distance, topology, and direction, or by their combination. In any case, the majority of research efforts have been focused on the computation of all spatial similarity determinants based on solely the quantitative scales by and added up to overall similarity after the normalization of each determinant (Gudivada, 1998). As it becomes apparent all these efforts has been mainly focused on the strict comparison between objects of a scene with the aid of their geometric matching, searching for commonalities (intersection) and differences (non-intersection) where the shape and metric information are the primary components. As it has been found, there are a number of limitations deriving from such a deterministic approaches. For instance let us consider the case of a scene-matching task where the area of interest where the scene similarity will be based on is an airport acquired from satellite imagery. A typical scene matching procedure is based initially on the extraction of the features of a scene. This step is very critical for the final outcome considering two different scenarios; the over-extraction, and the under-extraction. Both cases lead to a problematic description of the scene resulting in a very ambiguous scene matching procedure since it is very depended on the extraction quality. To this extend, scene-matching task can become also very confusing in cases also where physical changes of the feature itself have occurred.

Figure 1.1: Example of a spatial scene as a composite structure comprising built objects in a satellite image.

Another critical issue is the variability in geometries (i.e. shape, dimensions) as well as the distances of a specific taxa of objects that describe a spatial scene. That becomes essentially critical when the scenes to be compared belong to completely different locations in terms of context. For instance in the case of airports in Figure 1.1, although each airport has some sort of configuration up to a certain point, each major components may significantly vary with respect its functionality, and its location. According to all the above mentioned, it becomes apparent that a purely quantitative modeling of the spatial configuration of a scene based solely on metric information of its key features, imposes a number of constraints to similarity task, leading to limited results. As it becomes obvious, in order to have a more holistic and therefore more effective spatial scene similarity it is of essential importance to consider the scene as a whole and incorporate its semantics that can provide us with higher-level information.

Although scene matching and identification has received a great deal of attention in the past two decades, event detection and classification in social media creates new scientific questions considering the fact that the level of complexity and the heterogeneity of factors that are involved demand a completely new design of methodologies. Therefore the task of scene similarity in such cases where a scene is comprised by conceptual objects that form an event is still unexplored. The main focus is now shifted to the need to understand how such complex and high-level semantic information can be represented in an efficient yet accurate way. An event in social media can be considered as a semantically meaningful human activity that occurs in geographical space, which comprises of a scene that contains a set of objects. In such case a scene the refereed objects do not necessarily refer to human infrastructure of physical landscape but they represent abstract notions of human activity related to the specific event that have semantic meaning. Scene interpretation and identification then can be implemented by monitoring abstract notions of events, location and crowd-sourced responses. Based on that, the opposite becomes also true; what if the semantic components of an event can be analyzed in objects that have geospatial properties that can resemble a scene? If that is true it means that event detection in social media can be converted to a scene understanding and similarity-matching task. An example of this case is illustrated in Figure 1.2, which shows Cairo's Tahrir Square in Egypt, where large groups of protestors have demonstrated and celebrated the expulsion of Mohamed Morsy.

Figure 2.2: Example of a spatial scene as a composite structure comprising crowds in an event.

Before we proceed with an assumption such as the aforementioned, it is important to define the concept of a scene when it comes to event detection in social media. According to Fei-Fei and Li (2010), in order to achieve an event categorization and eventually detection in a semantic level it is essential to be able to answer three W's; *what* (the *event* label), *where* (the *scene* environment label) and *who* (a list of the *object* categories). In a similar fashion we adapt this conceptual framework in order to decompose an event to its contextual parts, to show the interdependence with the scene, and to try to model it by using characteristic relations among its objects. At this point it is important to examine what are the objects that comprise a scene on an event. Although a scene in social media has a geographical context, it consists of a conceptual abstraction of a well-defined physical space where its borders are definite. A scene is created during the occurrence of an event according to the human activity that this event attracts.

In other words, contributors define a scene and their semantic notion is that which creates the objects of that scene. The semantics in such case consists of contributors' reports that have spatial and temporal context given the fact that an event occurs in a given time range and concerns a broad (or specific sometimes) location. Wayant et al., (2012), found that these semantics can be organized into spatiotemporal clusters that summarize the spatiotemporal semantics of the event. Therefore, these clusters by emending all the semantic information based on their spatio-temporal extent can be considered to be the objects that comprise a scene and consequently describe an event.

Based on that, it becomes apparent that there is a need for a conceptual kind of modeling in order to assess and identify patterns among these objects. What has to be taken under consideration though is the vagueness that is incorporated in such concepts. De Longueville *et al*. (2010), which addressed the vagueness in crowdsourced information, stated that a concept is known as vague if at least one of its characteristics does not obey to Boolean logic. That statement can be retrieved back to the work presented by Fisher (2001) where he used the *Sorites Paradox* (or paradox of the heap) to explain the vagueness in the geographic space (see also Barker, 2009). According to this paradox, by trying to answer the question “how many grains of sand do we need to have a heap of sand” we won’t be able to have a meaningful answer if we will be based on strictly numerical calculations. For example Boolean logic in this case which dictates a threshold value where if the number of grain is larger than this value then this is considered a heap otherwise it is not, is not applicable.

The same discipline applies also in the case of spatio-temporal clusters where there is no definite boundary, size and shape since their meaning has semantic value. For example how can we set a threshold value on the distance *D* between two cluster A and B where if distance between A & B < *D* then A is close to B while if A & B > *D* then A is close to B? Would be meaningful a single meter to effect significantly the spatial relationship between these two clusters? Hence, in order to enable the description and the modeling of patterns created among clusters of crowd-sourced information it is essential to tackle this issue under the prism of Fuzzy Logic. On the parallel, as it was stated by Vatsavai et al., (2012), spatial (topological) relationships consist of high level descriptors that capture the semantics and can efficiently discover and model patterns in complex objects. Under all the aforementioned considerations, the proposed methodology for scene matching appears to have great potential to be applied in a case of an event scene created by social media feeds. Its potential relies on the fact that is based on the extraction of topological and directional relationships in the context of qualitative spatial reasoning based on fuzzy logic measurements which provides quantitative results that are necessary for the purposes of scene matching.

With respect the information that can be extracted from such a task, it becomes challenging to compare patterns of response in social media in order to assess whether these scenes are identifiable and therefore whether there is a spatially relevant character behind them. The challenge when considering this type of application is that we do not know whether these scenes actually do have an identifiable spatial pattern associated with them. Whereas in an airport form follows function, and this leads to topologically consistent arrangements, nobody knows whether responses to an event actually follow any such reason. The successful application of this task may lead to event detection in social media based mainly on spatial and geometric patterns among similar scenes. Furthermore an indirect application at the direction of event detection could be to detect an anomaly, which denotes the burst of a new event. As an example by monitoring the spatial signature, created by the fuzzy spatial relations, of a scene in a time frame (i.e. per day), a sudden change of the signature could indicate the creation of an event. To this extent, detecting data patterns in anomalies also facilitates to anticipate future activity and this way to predict the type of a future event.

1.3 Research Hypothesis

Based on the above-mentioned challenges and limitations the following research hypothesis is formulated for this dissertation:

Given that a scene is a composite structure, comprising individual key components (e.g. objects) as they are arranged in space, a semantic similarity measure based on abstract spatial relations of these objects by combining topology, direction, and distance can provide us with a more descriptive spatial signature of each scene and better support scene similarity assessment in diverse applications.

1.4 Research Hypothesis

According to the hypothesis the present dissertation is addressing three key components:

- The algorithmic development of techniques for a robust comparison of spatial scenes based on the topological and directional arrangement of objects within them by incorporating fuzzy spatial relations.
- The use of these techniques to compare composite scenes comprising built objects using satellite imagery.
- The use of these techniques to compare patterns of response in social media feeds in order to assess whether these scenes are identifiable, and therefore whether there is a spatially relevant character behind them.

1.5 Intended Audience

This dissertation is intended for researchers and developers primarily from the GeoInformation Science community, including fields such as Remote Sensing, Geographic Information Systems, Volunteered Geographic Information, and Geographic Information Retrieval. The audience also includes experts from the fields of Computer Science, Computer Vision, Human Computer Interaction, and Artificial Intelligence as it relates to the intelligent retrieval of semantic information. In general we believe that this work will be of interest to scientists interested in scene matching, similarity assessment.

1.6 Organization of the Dissertation

According the structure of the present dissertation each chapter builds on observations and findings of previous chapters. The assessment of previous research, the evaluation of the hypothesis, the test cases, and the conclusions are each assembled in separate chapters. The remainder of the thesis is structured as follows:

Chapter 2 reviews the research efforts that have done in the past, and presents the state of art in the specific domain. The ideas, technologies, and methodologies devised up until recently for the task of scene similarity are discussed and their limitations are emphasized pointing out this way the challenges that the present effort manages to overcome. New findings from the domain of geo-semantics and qualitative spatial representation and reasoning are discussed as well as the importance of fuzzy set logic in conjunction with the spatial relations which they comprise the theoretical basis of the proposed methodology. A notion of the necessary background theory is tacking place in this chapter with respect the various fields that are involved. It has to be noted that a basic understanding of the main concepts of these fields is prerequisite for the reader, in order to understand the present work.

Chapter 3 outlines the proposed framework for the scene similarity assessment. Each section of this chapter explains the theoretical foundations that were used for the synthesis and implementation of the main similarity algorithm. Specifically, the chapter begins with a brief description of the followed approach and continues with the justification of the selected types of spatial relations and their fuzzification. Also the main methodology of Histograms of Forces used for the modeling of the fuzzy spatial relations are presented and are explained of how they successfully manage to incorporate topology, direction, distance information. The chapter concludes by the illustration of the similarity metric that is proposed, which essentially manages to extract higher-level information from the scene via a qualitative measurement while it concludes in comparable, machine-readable quantitative results that are necessary for the purposes of a meaningful scene matching.

Chapter 4 presents the first of the two test applications according to which our proposed framework is being applied in the case of a built, structured environment such as airport scenes from satellite imagery for the entire African continent. Specifically, an ontology-driven scene similarity is implemented based on the concept of a prototypical ontology / airport.

Chapter 5 extends the findings of Chapter 4 to a completely different test case scenario in terms of data source as well as what a scene can also be. Specifically the second test case consists of an unstructured spatial scene, comprised of social media feeds for an emergency event. In this case the scene similarity procedure is not per se solely ontologically driven but is using the context of the first case to apply it to a more abstract ‘objects’ under the viewing angle of conceptual space.

Chapter 6 concludes the dissertation by providing with a summary of the tasks that have been accomplished as well with a discussion of the major results, with respect the proposed methodology, and highlights the most important contributions of this study. Also it speculates on possible extensions of the present work and future research directions and outlook.

CHAPTER 2: CURRENT STATE OF THE ART

While quantification of spatial arrangement is a widely researched field in the application of scene similarity incorporating spatial relations in geographical information science, its effectiveness has proved to be limited due to the *semantic gap*. This chapter, which serves as a literature review, presents and reviews the background theory of scene similarity and it's semantic notion in Sections 2.1 and 2.2, while on Section 2.3 and 2.4 are explained the importance of Qualitative Spatial Representation and Reasoning as well as of Spatial Relations. In Sections 2.5 and 2.6, the importance of Fuzzy Sets and their contribution to the spatial relations and semantic scene similarity is addressed.

2.1 Scene Similarity

One of the most challenging tasks in the field of Geoinformatics is that of scene similarity, which still is in progress as new data and new representations of them have to be explored. Due to the importance and the diversity of this task, it consists of an interdisciplinary research domain with a variety of applications stemming mainly from Remote Sensing (RS), Geographic Information Science (GIS), Computer Vision (CV), and Geographic Information Retrieval (GIR) domains. Originally the research for the notion of similarity was initiated in psychology where the objective was to determine why and how people are grouped into categories and the reasons why some categories are more or less similar to each other (Medin *et al.*, 1993; Goldstone and Son, 2005). According to Edelman (1995), in human cognition, people are able to respond intelligently faster and with greater success to a stimulus that they retrieve from previous responses that have been made under similar circumstances. That indicates that similarity holds a fundamental role in human cognition since it consists the capstone in an individual's learning ability by classifying similar entities and by reasoning on similar situations. Gardenfors (2004) proposed conceptual spaces as a cognitively credible framework for the spatial representation of information that humans perceive, at a conceptual level, which can be modeled and quantified.

In the broad field of Geographic Information Science (GIScience) a scene is considered as an aggregation of spatial objects in a specific spatial arrangement. The majority of efforts in the past in the direction of scene similarity have been focused mainly on the content of the scenes giving less attention to the spatial context which is able to describe a scene more comprehensively and to lead to a more integrated scene matching based on the scene semantics. The typical image interpretation and pattern recognition methodologies that can be found in RS and CV communities tend to be confused at the moment of distinguishing between two visually similar, though conceptually different objects. This problem is referred to the literature as the "semantic gap" according to which there is a gap between low level information, derived from automated feature extraction, and higher level knowledge representation that applies in a specific spatial context (Ehrig, 2007; Hare *et al.*, 2006). Another definition about this problem was given by Smeulders *et al.,* (2000) according to which the semantic gap is "the lack of coincidence between the information that one can extract from the visual data and the interpretation that the same data have for a user in a given situation''.

In order to facilitate an approach that will incorporate the semantic information within a structured way, recent developments in the in the field of knowledge engineering have introduced the notion of ontology. By definition (Gruber, 1992), an ontology entails an explicit specification of a conceptualization, which consequently leads to a description of an abstract model. A critical issue to this point is the development of sufficient metrics in order to appropriately describe the spatial context of an ontology feature class so as to create a spatial configuration signature. That could lead to an ontology driven scene similarity where ontology can be used as a pattern to compare and analyze other similar occurrences of that feature class in other geospatial data sets (Clark, 2012). One issue that arises in this case is that a strict scene matching based on the ontological approach is not applicable since quantitative metrics cannot describe sufficiently a feature class.

That becomes critical especially in cases where no metric information is present and/or the scenes to be compared, for example using satellite imagery, are of different scale, and orientation. Furthermore despite the complications that a rigid scene similarity based on metric information might cause in the case of scenes in built environments using satellite imagery, it can become even more complicated in cases where spatial information can only be described in terms of semantics and context rather than the content. For example the case of a scene which is comprised of crowd-sourced information about an event using social media, although the components of this scene have geographical extend, the location information, still these components cannot be described in terms of shape, size, distances etc. The solution to this issue can be found in the field of spatial reasoning according to which higher knowledge representations like ontologies can be modeled through the spatial relations between the objects that comprise a feature class.

Although many ontological frameworks exist that incorporate spatial relationships (Bateman and Farrar, 2004), there is an inadequacy on the way that these methodologies handle the vagueness and the subjectivity of the spatial information. The above-mentioned semantic gap can be bridged with the progress made in the field of Qualitative Spatial Representation and Reasoning (QSR), and fuzzy set theory in the direction of spatial modeling (Wang *et al.,* 1990). The objective of the dissertation is to develop metrics for scene similarity assessment using abstract spatial relations among the objects comprising a scene, in the context of an ontological approach for the purposes of scene matching and ontology classification. Therefore we consider that abstract spatial relations are more important than absolute and/or quantitative spatial relationships in deriving semantic features for the means of an ontology driven scene similarity.

2.2 Semantics in Similarity

Recent developments in the research field of similarity propose measures that are not limited to exclusively structural methods or to basic network procedures within a subsumption hierarchy (see Blanchard *et al.*, 2008). Although the goal is to identify exact matching, often the goal is to evaluate whether two objects have sufficient amount of common characteristics by looking for similarities in order to justify that the two objects originate from the same principle class of objects. In semantic similarity the main objective is to calculate the theoretical intersection between abstract concepts and associations (i.e relations) and therefore constrict the gap between similarity and analogy. This difference is referred to as "semantic" similarity measures. According to Rosche (1978) a similarity assessment can be considered principally as a classification task. Attributes are used as the base to classify objects in a taxonomy, which permits us to assess the semantic proximity between each taxa in that taxonomy, in the conceptual space and not necessarily on the geographic space. Due to this fact it becomes evident that we need to incorporate qualitative decisions about the degrees of similarity. Therefore as it becomes apparent, this kind of reasoning in similarity measurement provides bigger eligibility in information retrieval and classification tasks than in the case of subsumption based approaches.

Janowich (2013) has stated the benefits of semantic similarity reasoning in managing with applications that incorporate fuzzy or ambiguous inputs derived from either human beings or from software agents. Despite the fact that this direction has attracted many researchers the implementation and interpretation of semantic similarity measures explicitly still remains a challenging task. Among the challenges, some questions that still need to be answered are, what is the appropriate theoretical foundation which can support what they measure, what kind of comparison can be between them, and which of them are more suitable for a specific application. Originally semantics as a subject was initiated in philosophy as the mean to designate the relations between major concepts as well as the perception of human beings. One of the most seminal works in this field with respect the semantic similarity notion can be find in Tversky's (1977) early work where he explained how human perception is based on a continuous search for similarities in objects and concepts. In the same direction, Gärdenfors (2004) introduced the notion of "conceptual spaces" where he described how human perception and description of the world, and especially about spatial environments, could be explained and be modeled by the aid of graph theory and eventually be quantified. Also he extended the notion of geographic space into the "conceptual space" by affirming that the mechanism where human perceives the spatial patterns in graphs and diagrams is similar to the one that is used in the 3-dimensional space at the physical world. The seminal work of Frank (1997) about the spatial ontologies provided an important linkage between the notion of semantics and geospatial information by explaining the uniqueness of geospatial data with respect their usage as semantic descriptors.

During the mid of 1990s a new research direction was initiated, under the term "geo-semantics" or "geospatial semantics", by MUSIL (Muenster Semantic Interoperability Lab) in Germany and the NCGIA (National Center for Geographic Information and Analysis) Research Initiative # 10 (Spatio-Temporal Reasoning in GIS) of the University of Maine[1]. The main objective of the field of geo-semantics is the study of context of geospatial data witch assembles technologies from various fields such as

[1] http://www.ncgia.ucsb.edu/research/initiatives.html

Geoinformatics, AI, cognitive science, spatial databases and the Semantic Web (Kuhn, 2005). According to the extensive research that Janowicz *et al*. (2013) have conducted to this direction, geo-semantics enable a plethora of methodologies that vary from top-down knowledge engineering and logical deduction to bottom-up data mining and induction by combining knowledge engineering with methods specialized to GIScience such as spatial reasoning, and geographic information analysis. One of his main contributions in his research about geo-semantics was that of its application in geospatial similarity. Specifically he enabled semantics-based geographical information retrieval by using semantic similarity and analogy reasoning (Janowicz *et al.*, 2014). As Bhatt and Wallgruen (2013) have reported based on their extensive work on spatial cognition, representation, reasoning, and applied geospatial ontologies, the conceptual models in the direction of geospatial events' and processes' representation are gaining significant ground and proliferation since there is an extensive research focus especially in the last decade. There is a plethora of specific interest in the areas of geospatial semantics and taxonomies of geospatial events and geospatial processes under the spectrum of ontological methodologies and into the nature of processes in a specific spatial context (Galton and Mizoguchi, 2009; Hornsby and Cole, 2007; Worboys and Hornsby, 2004).

Before we proceed with a further explanation about the application of geo-semantics in scene similarity, also refered as semantic scene similarity, it is important to clarify what is so special about geo-semantics in geographic information and which is the motivation behind that. One of the first works addressing this critical issue belongs to Harvey *et al*., (1999), where as they mentioned geo-semantics is an essential component for the needed interoperability of geospatial data and services so as the geographic information systems and services to have the capacity to function together without the need of human intervention. By achieving a sufficient degree of semantic interoperability it enables us to determine semantic similarities between concepts that are not limited to specific data structures and/or data sources. That becomes apparently true if we consider that although geographic information is based on the physical world there are many different conceptualizations that can describe the same physical processes or scenes. One can argue that geographic information is process-oriented and it spans across various levels of granularity. In the past this kind of data and functions have been processed and analyzed based on local understanding and properties. Nowadays though the geospatial data are distributed throughout the world, stressing out this way the importance of interoperability and common understanding in order to be able to be compared. Hence the question of how we can make GIS to retrieve autonomously the correct geospatial data and consequently find the necessary similarities among them without the subjective human intervention can be answered via the aid so geo-semantics.

While the traditional similarity measures try to examine why and how the entities of a scene are grouped into categories and consequently are less or more comparable to each other, the main difference in semantic similarity is that this comparison is implemented between higher meanings in contrast with a purely structural comparison. Hence in this case the challenging task is to specify the appropriate “language” to express the nature of these entities as well as the necessary functions in order to determine the conceptual closeness of the compared entities rather than using rigid measurements that could lead in inexact matches due to it’s lack of sensitivity. According to Janowicz *et al.* (2008), there are four core characteristics that should be taken under consideration in any measurement model in semantic similarity;

- *Properties of Semantic Similarity*: In semantic similarity measures symmetry, transitivity, triangle inequality, and minimality are not always valid computations, for example if A is similar to B and B is similar to C it cannot be assumed that A is similar to C. Therefore in the majority of developed semantic similarity measures similarity is defined as an asymmetric relationship.
- *Semantic Similarity depends on Context*: Semantic similarity is meaningful only under specific context for particular use cases while there is no universal similarity measure. For example similarity between to entities A and B cannot be defined without the presence of a reference entity C in order to describe to what both A and B are similar.
- *Semantic Similarity depends on Representation*: The degree of similarity between two entities A and B is depending on the computational representation used for both of them, and therefore a certain similarity measure is obliged to a particular representation.
- *Semantic Similarity, Usability, and Cognitive Plausibility Comparing*: The computed similarity rankings of compared classed, and/or scenes have to have a some kind of correlation with human similarity rankings (Rodriguez and Egenhofer, 2004).

As it becomes apparent from the above mentioned core characteristics, the selection of an appropriate similarity measure is critical as well as challenging task since on the one hand it has to incorporate the context of a scene without focusing only to it's describing components / objects, and on the other hand to be flexible enough in order to avoid rigid computations (i.e Boolean values). As Sloman *et al*. (1998) pointed out a "concept is an idea that characterizes a set or category of objects", with respect GIScience can be paraphrased as follows; a geospatial concept is the description of an idea that characterizes a geographic feature type. According to the seminal work of Schwering (2008) in computational cognition of spatial objects and geo-semantics, there are two basic constituents of a conceptualization with respect the semantic similarity, which are the objects and the concepts. Therefore in our case a geospatial object resembles a single geographic feature. One of her basic arguments was that the semantics of geospatial objects and concepts are described by some special characteristics, properties such as shape, size and location. Significant emphasis though was given in relations and specifically to spatial relations between the geospatial objects and concepts as a higher semantic descriptor for the needs of semantic similarity. Building on this direction, spatial relations are considered the capstone of the semantic similarity framework that was developed for the purposes of the present dissertation. Also she proposed five fundamental approaches, models as shown in Figure 2.1 as a synopsis to semantic similarity among geospatial datasets:

- *Geometric Models*: They are based on the analogy of the semantic distance to the spatial distance, consequently similarity is calculated as a function of spatial distance. A representative geometric model can be found on Gärdenfors (2004).

- *Feature Models*: They are based on set-theoretic knowledge representation where the feature properties of a concept are Boolean. In this case two concepts are considered similar if only they have the same feature. A representative feature model can be found on Tversky (1977).
- *Network Models*: They are based on graph-theoretic approaches by using semantic networks for knowledge representation. A representative network model can be found on Rada *et al.* (1989).
- *Alignment Models*: Similarly with the feature models, the alignment models are based on commonalities and differences of the data with the difference that the latter embeds the relational structure of their properties. A representative alignment model can be found on Goldstone (1994).
- *Transformation Models*: In contrast with the above mentioned semantic similarity models where they describe the concepts based on their properties and relations as descriptors to define their similarity, the transformation models use an entirely reverse approach. Similarity in this case is defined by the number of transformations that are necessary to distort a concept in order to make it transformationally equal with another one. A representative transformation model can be found on Hahn *et al*. (2003).

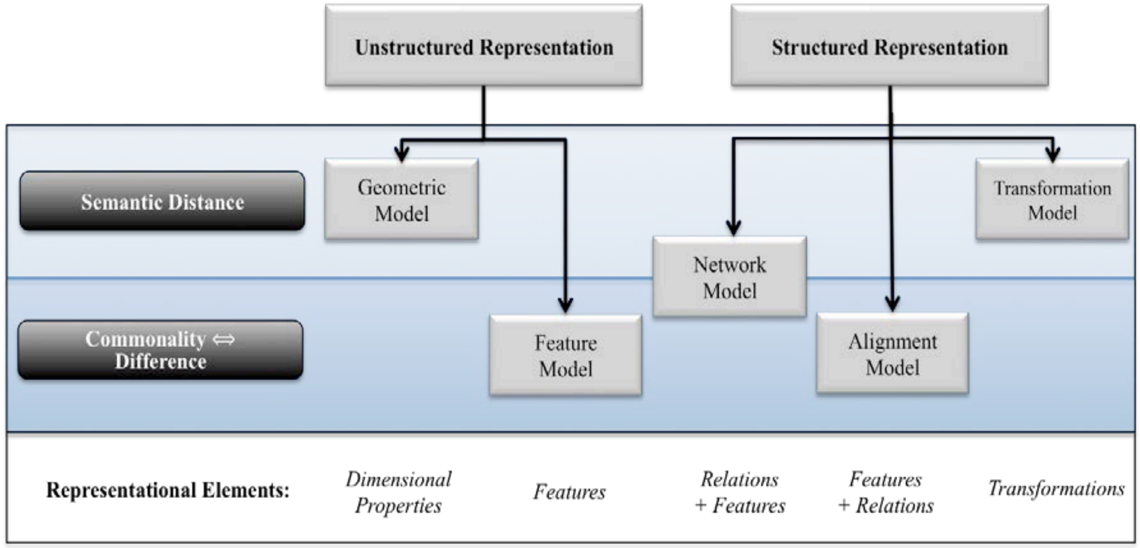

Figure 2.1: Semantic similarity measures according to different notions of similarity.

2.3 Qualitative Spatial Representation and Reasoning

One of the key challenges in semantic scene similarity is to find the appropriate spatial representation and calculi in order to successfully incorporate the semantics of a scene and therefore to implement similarity measures based on higher-level information. Cohn and Hazarika (2001) seminal work on the area of spatial representation and reasoning, have introduced the notion of Qualitative Spatial Representation and Reasoning (QSR) in the field of GIScience to provide adequate solutions in challenging tasks such as the one of comparing spatial scenes. QSR has been traditionally applied in CV for visual object recognition and robot's navigation by interpreting the results of low-level calculations as higher-level descriptors of a spatial scene since it enables the incorporation of the semantic of that scene (Fernyhough *et al*., 2000). As Cohn and Renz

(2008) stated, “the use of qualitative predicates helps to ensure that scenes which are semantically close have identical or at least very similar descriptions”.

The field of QSR involves abstraction methodologies and computational tools which address the representation and the reasoning about the space inside a non-metrical and formal frame (Freksa, 1991). This field has mainly evolved in AI (Stock, 1997) where spatial relations between objects in space consists the major component in this kind of knowledge representation. Rissland (2006) has pointed out the notion of AI in similarity. According to Cohn *et al.* (1997) the representation of QSR is based on the use of the spatial relations. A formal way to describe these relations given by the pre-mentioned author is; a relation *R* consists of a set of tuples *(d1,……,dk)* of the same arity *k*, where *di* is the member of the corresponding domain *Di* and *k* is the number of entities on which the relation is formatted. Usually, the spatial relations are binary and expressed with the use of algebraic operators like union, intersection, complement, converse or composition of them. In the application filed of QSR though, the main approach is to define a finite set of relations that is jointly exhaustive and pairwise disjoint (JEPD) since the algebra of relations provides an infinite number of tuples. Borrmann and Beetz (2010) addressed that the basis of any formal reasoning is the *calculus*, which is a system of rules that permits us to extract new knowledge from an axiom in a logically consistent way. In the field of QSR the main *spatial calculi* entails various qualitative properties and relations among spatial objects and concepts, predominantly such as topology, direction, orientation, and distance as shown in Figure 2.2.

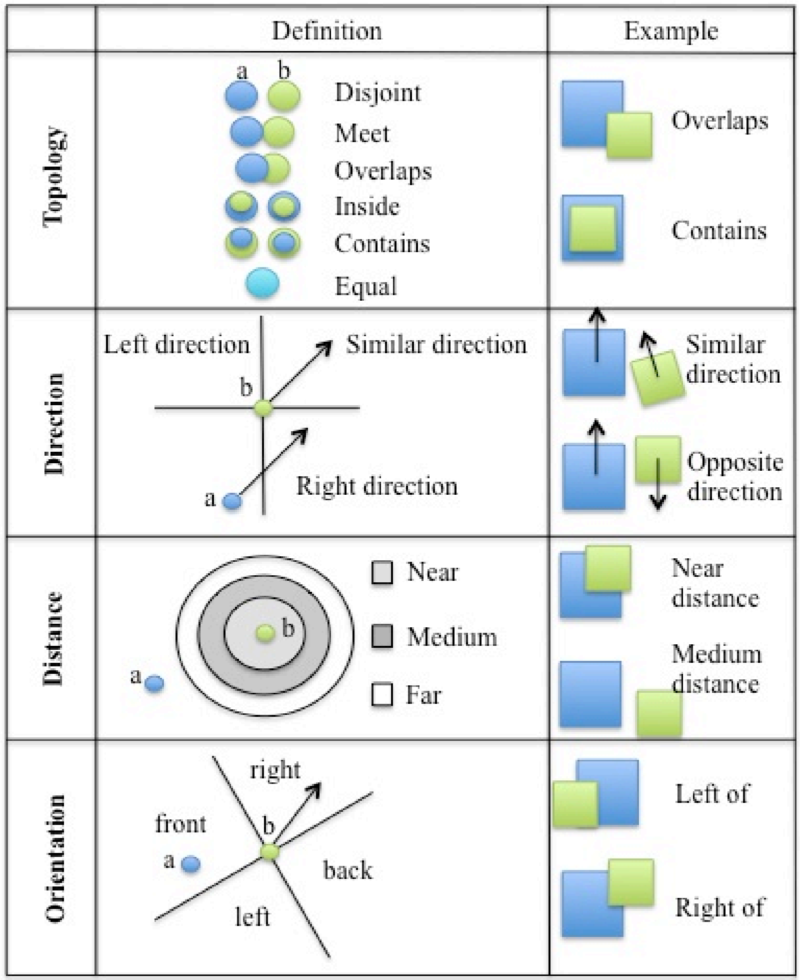

Figure 2.2: Definitions of qualitative spatial relations.

One of the most significant advantages that QSR provides is that this kind of reasoning and representation about the space is an abstract of the physical world, this way permitting computers to be able to calculate spatial relations of objects and/or concepts even in the case where quantitative information is absent or imprecise (Moratz *et al.*, 2011). While a quantitative representation bases the measurement of relations in a unit that is generally available and standardized (Freksa, 1992), a qualitative representation enables the characterization of the essential properties of the objects of a spatial scene and their configurations. That indicates the semantic notion of qualitative spatial calculi since this kind of descriptions is quite natural to human cognition. Frank (1996) also addressed the importance of qualitative spatial calculi by stating that although the qualitative approach is lacking of absolute precision it is able to provide us with a simplified deductive reasoning when precise information is missing. To this direction, Chen *et al*. (2013), based on the extensive survey on qualitative spatial representations that they have contacted, mention that qualitative relationships enable a quite natural representation of spatial situations among the objects of a scene hence QSR results to a fundamental approach on reasoning and representation of spatial knowledge.

There are three complementary aspects, which constitute the core of spatial-relation reasoning as stated by Egenhofer (2010), and establish a comprehensible basis for spatial and temporal reasoning. These are:

- The identification of a calculus for the description and distinction of various spatial relations. Current research effort in the field of QSR are mainly focused on closed sets of JEPD spatial relations so as there can be only one exact relation of any possible configuration that describes better this configuration. Consequently spatial relations result on the formation of an alphabet of an abstract language that is able to represent qualitatively any spatial configuration.
- The arrangement of the recognized spatial relations into their conceptual neighborhoods in order to acquire pairs of relations of highest similarity.
- The extraction of logical inferences that is necessary when common objects have

combined relations.

Despite the fact that a significant amount of theoretical research for the application and the benefits of QSR formalisms in GIS already exist, only a limited number of implementations have been incorporated in todays existing GIS systems. The technological advances in formal methods in the fields of AI, QSR and spatio-temporal dynamics lead to intriguing innovative viewpoints of *spatial informatics* as a basis for next-generation GIS systems (Bhatt *et al*., 2011). Current GISs as well as web-GISs evolve the management of vast quantities of spatio-temporal data related with environmental phenomena, remote sensing imagery, and recently crowd-sourced real-time information. The need of some or even all of these data to be combined becomes more critical suggesting the formation of a basis for a higher-level spatio-temporal analysis. Wallgrün and Bhatt (2011) pointed that the primary information theoretic modalities of the traditional GIS systems will undergo major changes while high-level ontological entities such as qualitative spatial relations, and the ability to represent and model them are expected to be the natural progression of next-generation GIS systems. The same vision is also shared from Cohn and Renz (2008) according to which next-generation GIS systems will be based on concepts that arise from Naïve Geography (Egenhofer and Mark, 1995) where QSR techniques are essential. Specifically they pointed out the problem of human-computer interaction according to which the given GIS systems are incapable to incorporate intuitive and/or common sense representations, preventing this way human cognition abstractions of the data and queries in a qualitative manner. Bennett (2008) with his work in QSR addressed also the issue of flexible query interpretation. Specifically, he emphasized the contrast between traditional GIS in which queries formation is based on a limited way depending on the way that data are stored in a database, and the flexibility that QSR provides by enabling more complex combinations. Also he discussed about another important aspect, the one of data consistency and integrity checking. For example it would be very useful to have spatial consistency constraints in a database such as “a railroad may not overlap with a building”. Although such constraints can be hand coded in a GIS, QSR provides the flexibility to formulate them with a spatial constraint language, which is more intuitive to the user, and therefore to create automatic inferences which allow more eligible detection of constraint violations.

Bhatt and Wallgruen (2013) highlighted two basic requirement that next-generation GIS systems should entail with respect the recent advances is QSR and in general the reasoning about objects, space and concepts. These are:

- *Knowledge engineering, semantics, and modeling*: Competence in incorporating abstractions of *objects, events, and processes* of spatio-temporal phenomena as native entities, which preserve rich semantic characterizations within an ontological and conceptual framework which allows interoperability between systems and implementations.
- *Analytical reasoning*: The computation of *high-level reasoning mechanisms* that are supported by the semantics of the formally modeled properties of domain-independent and dependent aspects.

Despite the fact that the domain of QSR has gained significant recognition in the field of GIScience during the recent years, the majority of the research efforts have been focused on the data modeling and on finding suitable measures of similarity (Chipofya *et al*., 2013). The appropriate utilization and formalization of abstract and/or qualitative spatial relationships for the needs of a spatial scene similarity still remains a challenging task in the research domain.

2.4 Spatial Relations

QSR and consequently spatial relations gained significant recognition in the last decade, increasing their spectrum of applications mainly because of the need to construct more precise and robust systems for scene description that would be of higher-level understanding. Although the quantitative spatial information is an important source, there are cases where this kind of information is absent or even not sufficient. This becomes critical in applications where the context is more important than the content and especially when the semantics are needed describe the multidimensionality and complexity of a 2D scene with a more holistic way. In order to accomplish an adequate qualitative scene description based on an ontological approach there has to be adequate spatial calculi. The completeness of spatial calculi that are used for this purpose is mainly depended on the qualitative spatial relations who describe one or more spatial dimensions (Bhatt, 2010).

There are three major spatial dimensions or alternatively three fundamental aspects of space where the majority of research in spatial relations has been based on. An important notice is that the scientific foundation to determine spatial relationships is computational geometry. According to Clementini and Di Felice (1997) spatial relations can be classified as topological, the directional (orientation) and the metric. Topological relations (Egenhofer, 1989; Cui *et al*., 1993) are based on the geometric properties of a 2D space and they achieve invariance in any topologic transformations (translation, rotation, and scaling). According to this important property also known as homeomorphism or topological isomorphism, even if two geometric objects have different shape or size, still their topological space will be equal. Directional relations (Freksa and Zimmermann, 1992; Papadias *et al*., 1995) are those that represent information regarding to the position of an object with respect to another and can be further classified as relative or cardinal. These relations are invariant to projective transformations by preserving collinearity and cross-ratio as well as invariant to scaling and translation but variant to rotations. Metric relations (Hernandez, 1991) are related mainly to angles and distances in the Euclidian space and are invariant to rotation or translation but variant to scaling. In the following table are presented the 3 fundamental spatial relations distinguished by their invariance under basic geometric transformations as shown in Table 1.

Table 2.1: Invariance of spatial relations under four basic transformations.

	Topological Relations	Directional Relations	Distance Relations
Rotation	✓	-	✓
Translation	✓	✓	✓
Scaling	✓	✓	-
Mirroring	✓	-	✓

According to the notions of each type mentioned above, it can be concluded that the only metric and/or quantitative relations can be defied quantitatively while the topological and directional relations are of qualitative nature and therefore consist the basis of QSR. In the following paragraphs are explained some of the most representative models for each of these three categories which have gained significant recognition especially in the field of GIS since they are considered foundational in spatial cognition (Klippel *et al*., 2013).

Topological relations: This category of spatial relations is considered as one of the most important since they can represent the essence of a spatial configuration (Egenhofer and Mark, 1995a). One of the most important reasons that this kind of relations is critical for applications such as the one of scene similarity is the fact that the constraints that they impose are mostly insignificant to subtle geometric variations. Also important is the ability to make qualitative distinctions among objects. The two most prominent and well-known model for topological representation and reasoning are the Region Connection Calculus (RCC) (Cohn, 1997; Renz, 2002), and the n-Intersection (Egenhofer and

Herring 1990; Egenhofer and Franzosa, 1991).

The *RCC* model is a first-order logic axiomatic theory of a set of eight binary topological relations and is based on a reflexive and symmetric primitive relationship between spatial regions C(x, y). In the literature, one can also found it as *RCC-8*. These are: disconnected (DC), externally connected (EC), partial overlap (PO), tangential proper part (TPP), nontangential proper part (NTPP), the inverse of TPP, the inverse of NTPP, and the Equal (EQ). One of the important advantages of the *RCC-8* is the large number of topological relations that can be derived by using this model as also their semantics in spatial configurations are made explicit. Figure 2.3 provides an illustration of the *RCC-8* continuity network with the 8 JEPD relations where the arrows resemble the sequence of the transitional relations assuming the continuous movements or objects' deformations. Bellow their formal definitions as well as their interpretations are presented.

$DC(x,y) \equiv \text{def } \neg C(x,y)$ "x is disconnected from y"

$PO(x,y) \equiv \text{def } O(x,y) \wedge \neg P(x,y) \wedge \neg P(y,x)$ "x partially overlaps y"

$EC(x,y) \equiv \text{def } C(x,y) \wedge \neg O(x,y)$ "x is externally connected with y"

$TPP(x,y) \equiv \text{def } PP(x,y) \wedge \exists z(EC(z,x) \wedge EC(z,y)$ "x is a tangential proper part of y"

$NTPP(x,y) \equiv \text{def } PP(x,y) \wedge \neg\exists z(EC(z,x) \wedge EC(z,y))$ "x is a non-tangential proper part of y"

$TPP^{-1}(x,y) \equiv \text{def } TPP(y,x)$ "y is a tangential proper part of x"

$NTPP^{-1}(x,y) \equiv \text{def } NTPP(y,x)$ "y is a non-tangential proper part of x"

$EQ(x,y) \equiv \text{def } P(x,y) \wedge P(y,x)$ "x equals y"

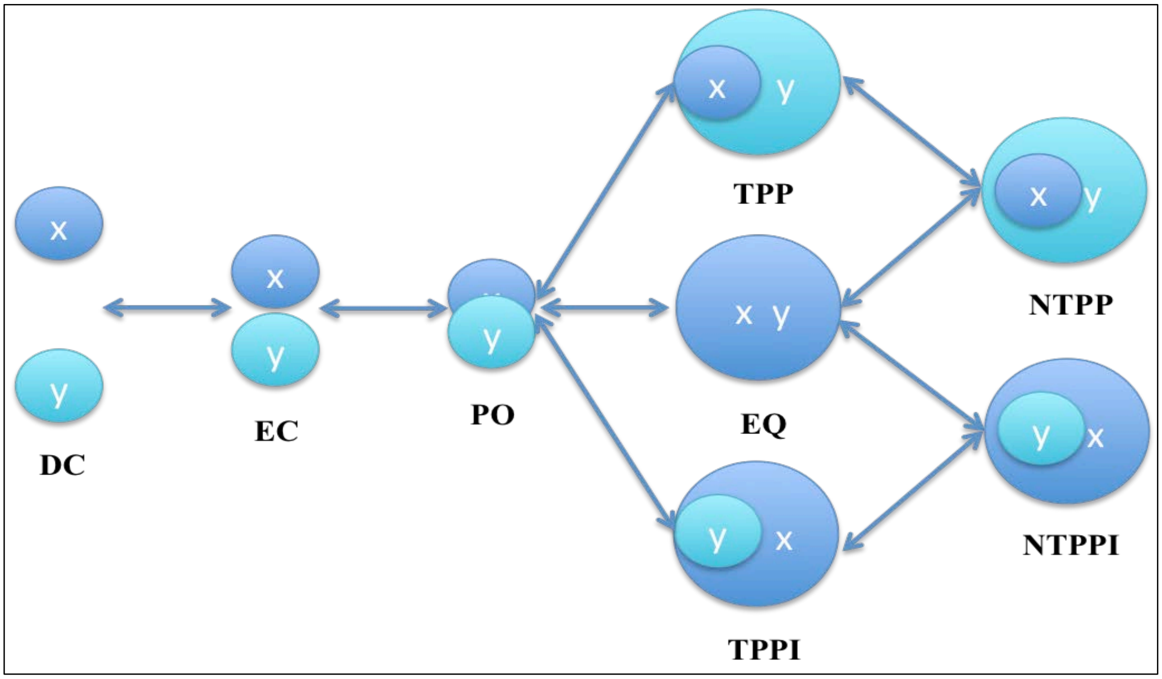

Figure 2.3: The RCC-8 continuity network or conceptual neighborhood.

The *n-Intersection* model is based on point-set topological theory where an object is described as a point set in a specified space $\mathbb{R}$ and indicates if the interior (x^o), which is the union of all open sets, the exterior (x^-), which is the set of all the points not contained in x and the boundary (θx), which is the intersection of the closure of x and the closure of the exterior of x, are intersect or not. In its simplest form, the topological relation between two 2D point set regions can be described by a 2×2 matrix also known as the four-intersection matrix or *4IM*.

$$R(x,y)\begin{bmatrix} x^o \cap y^o & x^o \cap \theta y \\ \theta x \cap y^o & \theta x \cap \theta y \end{bmatrix}$$

The *4IM* model later on was evolved to the 9-Intersection model or *9IM* in order to be able not only to classify relations between pairs of regions but also between all combinations of lines, point, and regions (Egenhofer *et al*., 1994). *9IM* identifies eight different relations between two regions, and nineteen relations between lines and regions as described by the following 3×3 matrix.

$$R(x,y)\begin{bmatrix} x^o \cap y^o & x^o \cap \theta y & x^o \cap y^- \\ \theta x \cap y^o & \theta x \cap \theta y & \theta x \cap y^- \\ x^- \cap y^o & x^- \cap \theta y & x^- \cap y^- \end{bmatrix}$$

From the family of the *n-Intersection* models, nowadays the one that has been widely used and established as the basis for queries and assertions in the most popular GIS spatial database suites is the one proposed form Clementini *et al*., (1993), as an extension of seminal works of Egenhofer, known as *DE-9IM*. The "dimensionally extended" *9IM* can describe 512 possible 2D topological relations using a Boolean matrix domain. All possible combinations are grouped into eight spatial predicates: equal, intersects, disjoint, touch, within, contains, overlap, and cross. In Figure 2.4 as illustrated *DE-9IM* is shown while Equation 1 presents the 3×3 intersection matrix where the model is based on.

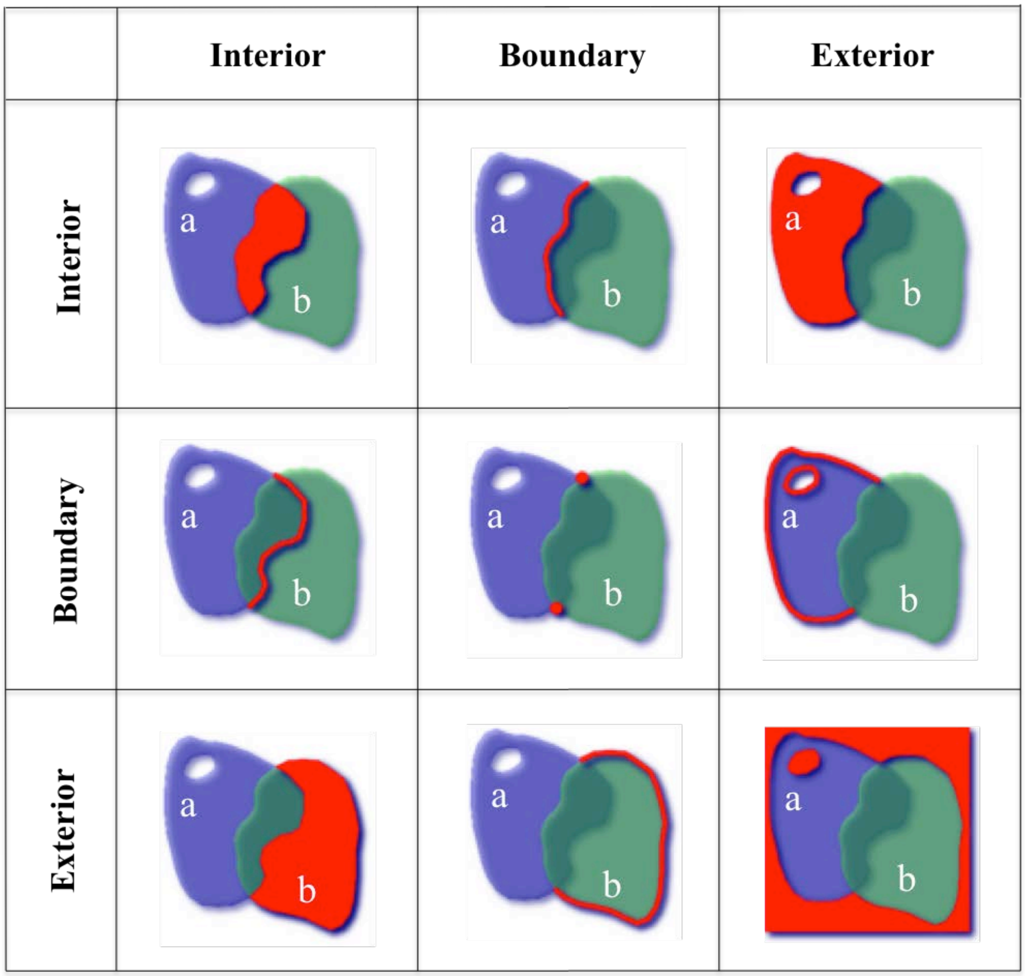

Figure 2.4: The *DE-9IM* for two overlapping polygonal geometries a and b.

Equation 1: The* 3 × 3 *intersection matrix of DE-9IM.

$$DE9IM(a,b) = \begin{bmatrix} \dim\big(I(a) \cap I(b)\big) & \dim\big(I(a) \cap B(b)\big) & \dim\big(I(a) \cap E(b)\big) \\ \dim\big(B(a) \cap I(b)\big) & \dim\big(B(a) \cap B(b)\big) & \dim\big(B(a) \cap E(b)\big) \\ \dim\big(E(a) \cap I(b)\big) & \dim\big(E(a) \cap B(b)\big) & \dim\big(E(a) \cap E(b)\big) \end{bmatrix} \quad (1)$$

Directional relations: As Frank (1991) stated, the directional, or as referred to the literature, cardinal spatial relations describe qualitatively the orientation between two objects. The directional calculi are based on the assumption that a spatial object is placed relative to another one, by involving three principal elements: the target object, the reference object and the reference frame. Due to this fact, directional relations are more constrained than the topological ones but less than metrical information. Among the various directional representation models that have been proposed, two of the most commonly known are the ones derived from Frank's work (Frank, 1991; Frank, 1996), named respectively the cone-shaped direction and the projection-based direction models. The first model is based on a cone-shaped calculus using four or eight disjoint sector of the space, which is divided by lines passing trough the reference point. The second model is based on a projection-based calculus using a horizontal and a vertical line across the reference point. An optimization that was derived by the combination of both of the previously mentioned models, was proposed by Isli (2004) namely *cCOA*, which also is considered to be closer to the human perception. Nowadays one of the most efficient directional models is the one proposed by Mossakowski and Moratz (2012) namely $OPRA_m$ (m is the number of lines passing through the points), which is able to incorporate information of different granularities in a single frame. In Figure 2.5 is illustrated the $OPRA_m$ model for a basic relation $x_4\angle_{13}^{3}y$ with m=4. In this example the oriented point x is placed on the 3rd part of the space that is divided by the lines passing through the oriented point y, while y is placed on the 13th part decided by x.

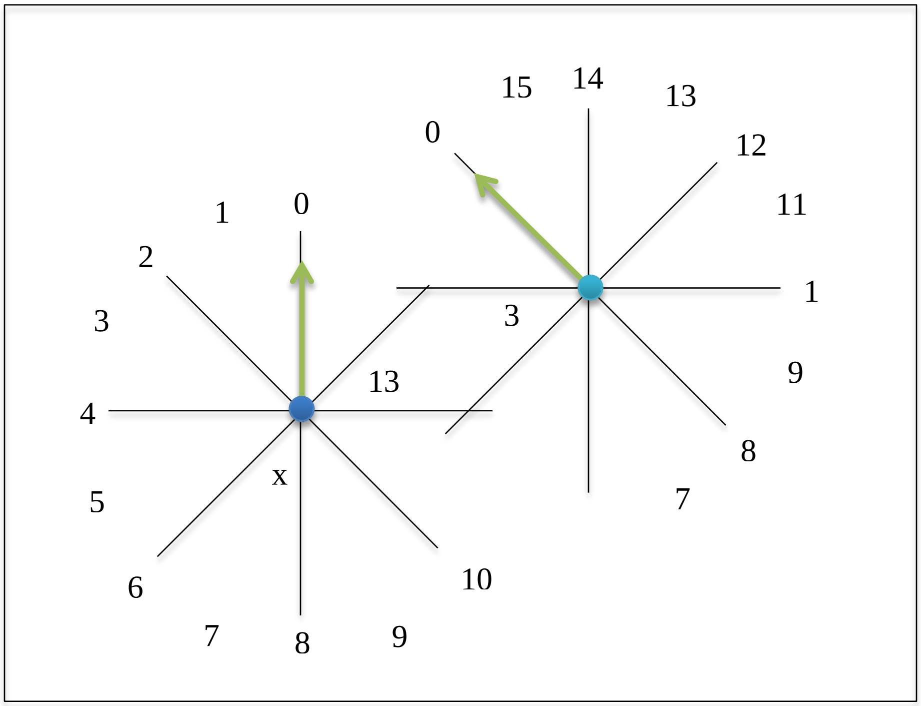

Figure 2.5: The OPRAm directional model for a relation $x_4\angle^3_{13}y$.

Distance relations: This category of relations is the less critical than the two previous ones since distance relations alone are not sufficient enough for reasoning. Usually, the existence of at least the directional relations is necessary in order to have a meaningful representation and reasoning. There are two main groups in this category; the absolute which are based on metric measurements between two entities, and the relative which involve the qualitative measurement of the distance between two objects with respect a third one. Some representative models in this category include the conceptual neighborhood graph for qualitative distance relations proposed from Burns and Egenhofer (1996) in which they define the relations 'zero', 'very close', 'close' and 'far'. Also, Clementini *et al*. (1997), used a combination of cone-shaped direction and absolute distance, Zimmermann and Freksa (1996) combined the Delta Calculus with a point-based directions, and Liu (1998) who proposed the qualitative trigonometry and qualitative arithmetic distance model. One of the most promising models nowadays is the ternary point configuration calculus (*TPCC*) proposed by Moratz and Ragni (2008), where it combines direction, using a double-cross calculus, with distance based one the two of the three points, resulting is 27 atomic JEPD relations. Figure 2.6 illustrates the reference system used by the *TPCC* model where f, b, l, r, s, d, c stand for front, back, left, right, straight, distant, and close.

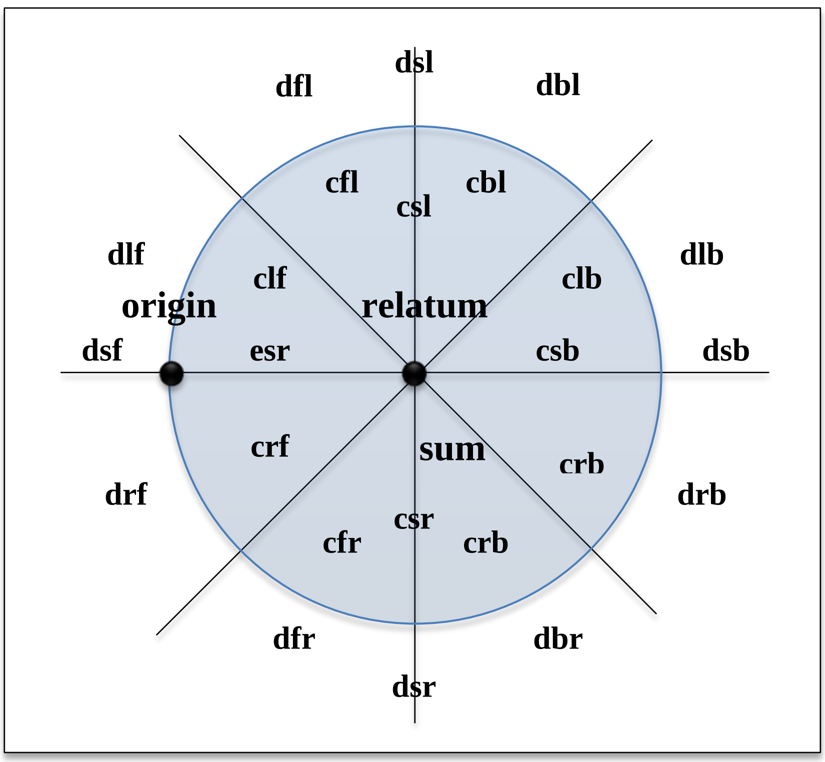

Figure 2.6: The reference system of the TPCC directional relation model.

As it becomes apparent from the aforementioned research efforts in the direction of spatial representation and reasoning and especially the various spatial relation models, there are still two notable limitations with respect the “features” on the terrain. According to Clark (2012) these are:

- ✓ The ineligibility of basic topological relation models such as *9-Intersect* and *RCC-8* to incorporate spatial calculi between different geometric primitives. For instance in the two above mentioned models the calculations are implemented on area/area, area/line, and line/line while a real scene will require calculations such as line/area and/or point/area etc.
- ✓ Due to the fact that these models are based on fundamental geometric computations using a defined set of primitives, it could be problematic in applications where abstraction of features is essential or the actual features are abstract concepts.

2.5 Fuzzy Set Theory and Spatial Relations

Although the present GIS systems provide a considerable number tools that enable spatial analysis based on relational models still are not adequate enough to incorporate the uncertainty as well as imprecision in modeling and decision support (Robinson, 2003). This becomes especially critical when metric information is absent or not sufficient. Stefanakis *et al*. (1999) addressed in detail the importance of equipping GIS packages with efficient tools, which are useful for decision-makers that are able to incorporate uncertainty of geographical phenomena. It becomes apparent that it is of essential importance to use alternative similarity measures to the traditional ones, which will stem from axiomatic theories. Fuzzy set theory (Zadeh, 1965) consists of one of the most sufficient solutions in order to avoid the above-mentioned limitations. As shown by Cross and Sudkamp (2002), fuzzy sets, are extensively used as a panacea for applications involving uncertainty, they provide with an ideal explanation for the challenging tasks of semantic similarity and similarity in general. Given the fact that similarity is inherently vague, it can find a natural expression in fuzzy set theory since the majority of its constituted components and inference mechanisms can sophisticatedly be described via the use of fuzzy concepts and operations, respectively (Nedas, 2006). Therefore it becomes feasible to find an applicable way to measure this uncertainty by utilizing some type of qualitative information that can be translated into quantitative metrics. The gap between the qualitative and quantitative measures was bridged with the progress made in fuzzy set theory in the direction of spatial modeling (Dutta, 1991). Fuzzy set theory can be considered as an extension to the classical set theory by replacing the deterministic nature of the later (1-true or 0-false) with the degrees of belief. Before we proceed with explaining the applicability of fuzzy sets in spatial relations and consequently to semantic similarity it is essential to explain some fundamental disciplines and/or preliminaries of fuzzy set theory.

Fuzzy Set Theory Preliminaries

As discussed above, classical set theory, which is based on the Boolean logic, considers an object as a member or not a member of a given set. For example for a given set D the membership degree to which an object *k* belongs to the set A can be expressed by the membership function μ_D that can hold two values, 0 or 1. Equation 2 shows the membership function in classical set theory, where b_1, b_2 are the boundaries of set A:

Equation 2: The membership function in classical set theory.

$$\mu_A(k) = \begin{Bmatrix} 1, & b_1 \le k \le b_2 \\ 0, & k < b_1 \; or \; k > b_2 \end{Bmatrix} \tag{2}$$

On the contrary, the basic concept in fuzzy logic domain is the representation of the degree to which an object belongs to a specific set. Based on that, an object can belong partially in a certain set S according to the degree of belief, which is the concept that was introduced by the fuzzy logic domain. Following to that, each set of objects S = {si} then produces a fuzzy set F_S, as shown by equation 3:

Equation 3: Fuzzy set (Fs) in Fuzzy Logic.

$$F_s = \{s_i, \mu_i \mid s_i \in S, \mu_{si} \in [0,1]\} \tag{3}$$

where μ_{Si} the degree of belief with value ranging [0,1] with 0 indicating no-membership and 1 indicating full membership (Vazirgiannis, 2000). In Figure 2.7 is illustrated a graphical example of classification representation of the direction between two objects A and B. So supposing the azimuth for the two objects indicates that their direction is west, where θ is the azimuth, the representation of the direction will be as follows,

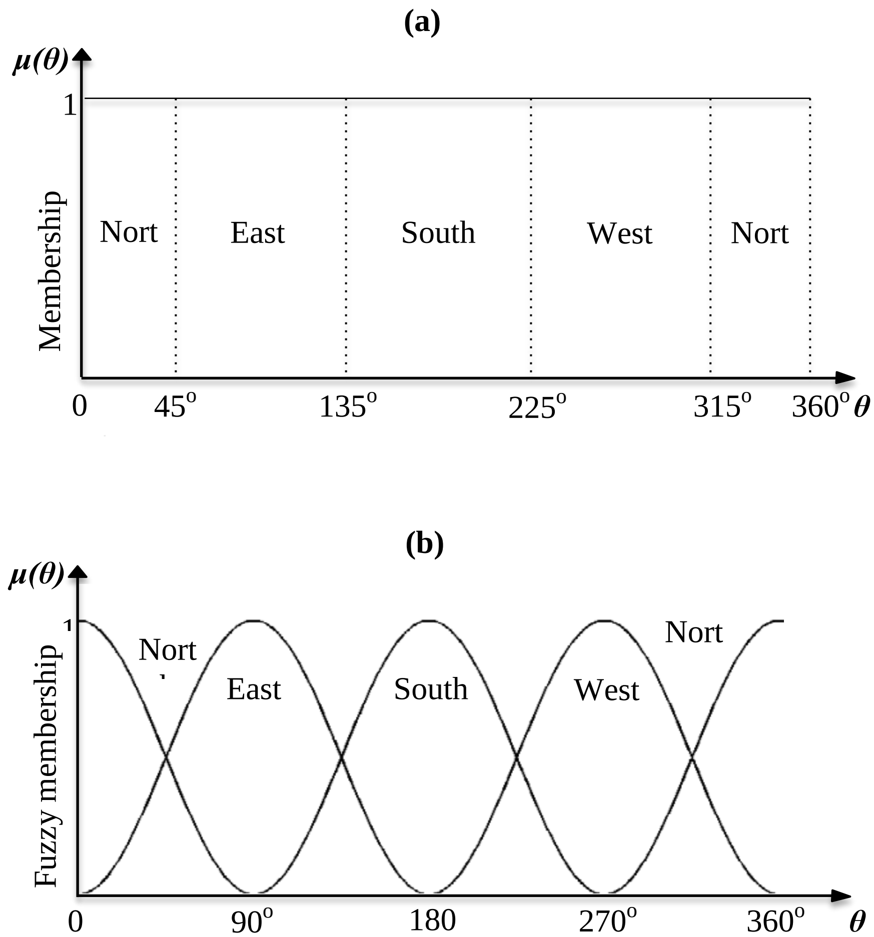

Figure 2.7: Classification of direction between two objects (a) based on classic membership function (b) based on fuzzy membership function.

Fuzzy Membership Function

One of the most critical steps in fuzzy set applications, which heavily affects the results of the decision-making process, is the selection of the appropriate fuzzy membership function. According to Burrough (1996), there are two major options available for selection the membership functions for fuzzy sets: (i) through an imposed 'expert' model; and (ii) by a data driven multivariate procedure. In the first category an a priori membership function is used which is based on expert knowledge for the assignment of a degree of membership to individual entities with respect a lexical value characterizing a theme. Therefore this method is also known as the *semantic import model* (SI) (Baldwin and Zhou, 1984; Robinson, 1988). Figure 2.8 illustrates several basic conventional linear models that are used as membership functions.

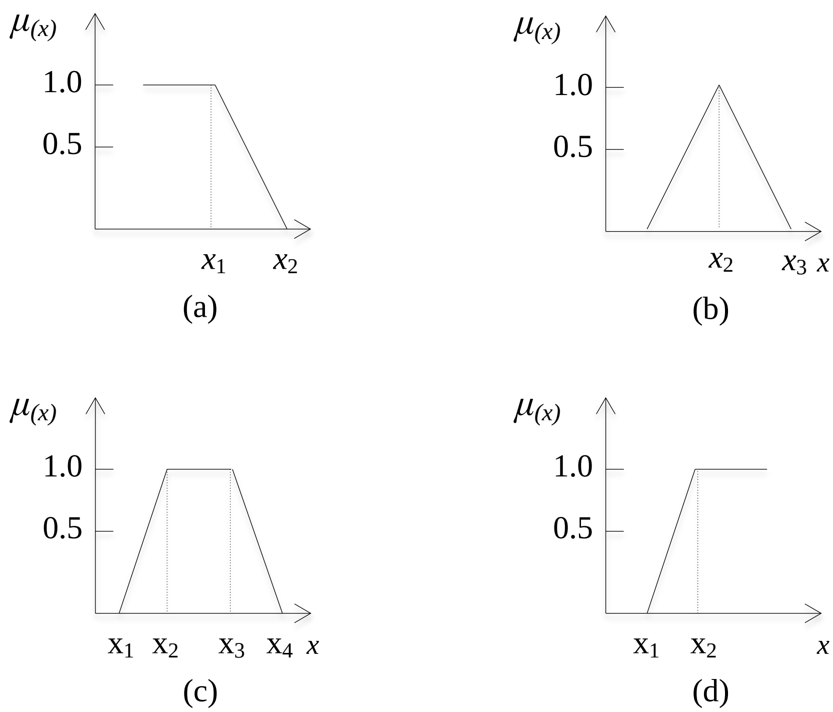

Figure 2.8: Basic conventional membership functions. (a) L Function; (b) ∧ Function; (c) ∏ Function; (d) Γ Function.

In the first category the selection of the membership function is data-driven, meaning that the functions are locally optimized to match the data. This method is also known as *natural classification model* and its principle is similar to the one of cluster analysis and numerical taxonomy (Kaufman and Rousseeuw, 1990). Independently from which of the two approaches will be selected, the critical issue is the form or shape of the membership function to be "human-like" and close to the reality. The definition of a *fuzzy set U* is based on the assignment to each element in the universe of discourse *U* a value from the real interval [0,1]. This degree resembles this element's membership to the fuzzy set and relates to the degree of similarity or compatibility of this element with the concept described by the fuzzy set (Klir and Yuan, 1995). The assigning function is actually the membership function μ_U of the fuzzy set U, expressed as $\mu_U: U \rightarrow [0,1]$.

Fuzzy Relations

There are a variety of degrees of association or interaction between objects that can be used in order to formulate fuzzy relations. Each specific function of a fuzzy relation leads to a specific degree of membership of tuples in the relation. Hence in fuzzy set theory each relation is represented as an *n*-dimensional membership array where each *n*-tuple corresponds each entry in the universal set and for each entry is assigned a value in the interval [0,1]. According to Zadeh (1971) who introduced the similarity relations in order to specify the degree of similarity between elements of a universe *U*, there are two important types of relations. The first one is the *fuzzy equivalence* or *similarity relation* that is symmetric, reflexive, and transitive and resembles a generalization of the crisp equivalence relation. The second one is *fuzzy compatibility relation*, which is similar to the first one except the fact that is not transitive (Sudkamp, 1993). In fuzzy set theory and reasoning there are three fundamental concepts with respect the relations, which are intersections, unions, and completes corresponding to three basic scoring rules for conjunctions, disjunctions, and negations (Equations 4a-c). As Klir and Yuan (1995) stated, “Since the fuzzy complement, intersection, and union are not unique operations, different functions may be appropriate to represent these operations in different contexts. The capability to determine appropriate membership functions and meaningful fuzzy operations in the context of each particular application is crucial for making fuzzy set theory particularly useful.”

Equation 4(a-c): The three fundamental relations in Fuzzy Set theory.

$$(A \cap B)(x) = \min[A(x), B(x)] \rightarrow \mu_{A \wedge B}(x) = \{\mu_A(x), \mu_B(x)\} \qquad (4a)$$

$$(A \cap B)(x) = \max[A(x), B(x)] \rightarrow \mu_{A \vee B}(x) = max\{\mu_A(x), \mu_B(x)\} \qquad (4b)$$

$$A(x) = 1 - A(x) \rightarrow \mu_{\neg A}(\chi) = 1 - \mu_A(x) \qquad (4c)$$

According to the extensive research that has been conducted by Bloch (2005) on the direction of the development and application of fuzzy spatial relations and according to a more recent study (Calegari and Sanchez, 2007) there are significant advantages for using fuzzy spatial relations to the ontological description. The advantages of fuzzy spatial representation arise from the ability to decrease the semantic gap between quantitative information obtained from an image and higher concepts that ontology contains. This representation permits essentially ambiguous and indefinite concepts such as “next to” to become integral aspects of a concept, especially when the semantics of such concepts are influenced by their environment and not solely by isolated objects. Hence it provides a rich framework for knowledge representation and spatial reasoning by avoiding the imprecision that might be caused by a deterministic approach of a subject-matter expert.”

2.6 Fuzzy Spatial Relations in Semantic Scene Similarity

As it was shown in the previous section, fuzzy set theory can play a critical role in the semantic similarity of spatial scenes since the degree of membership of a fuzzy set can be used a similarity measure. Therefore it can be considered that fuzzy set theory and semantic similarity are interrelated. These kinds of measurements can essentially be used to express the similarity and/or compatibility between a feature that belongs to a set and the basic concept that defines the set no matter if the concept is vague (i.e. *“next to”*). Hence the task of retrieving similar spatial scenes can be considered as a fuzzification of the classical information retrieval approach that was mainly based on searching for exact matches (Guesgen, 2002).

Although the coarse spatial relations (topological, directional, and distance) that have been used extensively so far in scene matching provide simplicity and intuition, QSR in combination with fuzzy set theory is able to provide a coherent relaxation of the relational constraints imposed by them (Nedas and Egenhofer, 2008). There are two significant weaknesses that can be introduced by these kinds of relations in scene similarity assessment. The first one is that deviations that small quantitative divergences may affect more the matching results than large quantitative divergences, rejecting this way the strong matches, while introducing less important ones. The second one is the incompetence of distinguishing among members of the same class, which may result to an assessment where all the relations of the same category to be recognized as equally similar. In Figure 2.9 are illustrated two examples that resemble the two above-mentioned limitations that coarse spatial relations present in a typical scene similarity assessment.

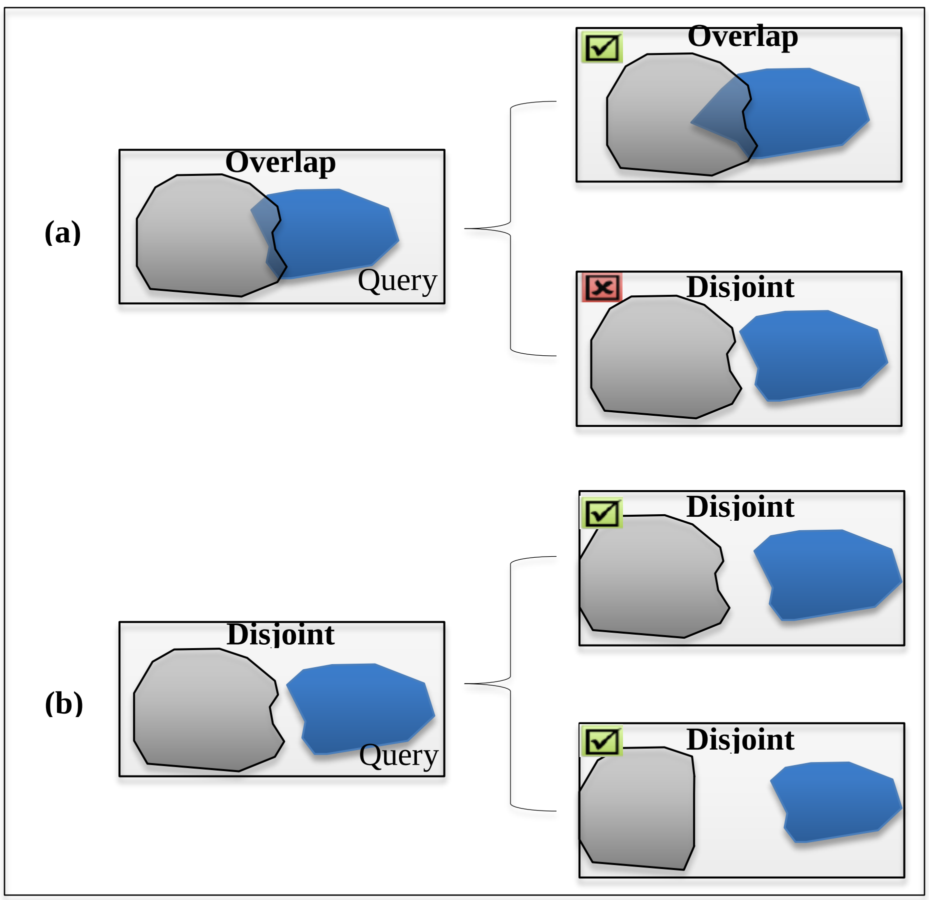

Figure 2.9: Limitations of coarse spatial relations in scene similarity assessment: (a) Coarse distance relationships in a conceptual graph may result in missmatching on highly similar candidates. (b) Incompetence of distinguishing among members of the same class resulting in equally similar.

Hudelot, *et al.* (2008) based on their extensive research in the direction of fuzzy spatial relations for spatial ontologies, have pointed out three key advantages that fuzzy representation offers enabling this way a bridge to the *semantic gap*. These are:

- The ability to represent the inherent imprecision of a concept. For example the concept “next to” which by it’s nature vague and imprecise, it’s semantics are depending on the scale of the objects, and the context in which objects are with respect their surrounding environment.
- The ability to embed expert knowledge for managing the imprecision with respect the concerned domain.
- The ability to formulate an adequate framework basis for spatial knowledge representation and reasoning, achieving this way the deduction of the *semantic gap* between symbolic concepts and numerical information.

Although fuzzy spatial relations in the context of a generic ontology can be successfully used in a variety of image processing tasks such as automated scene description (Keller and Wang, 2000), facial feature recognition (Cesar *et al.*, 2002), and medical imaging (Colliot *et al.*, 2006), our main concern in this dissertation is the use of fuzzy spatial relations for the representation of the structural knowledge of a scene for the purposes of semantic similarity. With respect the three major spatial dimensions / representations that were explained in previous section, what follows is their corresponding fuzzified definition.

For the fuzzy topological relations, according to Dubois (1980), there are three fuzzy set theoretic concepts, such as complementations *c*, t-norms *t*, and t-conorms *T* that can represent relations such as *conection* (i.e. intersects), *inclusion* (i.e. inside of), and *exclusion* (i.e. outside of) correspondingly. The fuzzification of topological relations is able to provide us with answers to questions such as whether the relations between two objects are satisfied or not and to what degree, and whether the relation of one reference object from the region of a conceptual space is satisfied to some degree. That becomes true especially in the case of inclusion and exclusion where they enable to define the degree of a fuzzy object that is included/excluded in another one. Concerning the adjacency between fuzzy sets, as Rosenfeld (1984) proposed, it can be defined using a non-symmetrical visibility concept or by a symmetrical way from topological concepts as proposed by Bloch (1996).

Concerning the fuzzy directional relations, given the fact that this type of relations is inherently ambiguous and inexact, event in the case of crisp objects, the application of fuzzy sets can provide the best possible solution. The fuzzification of these relations enables a more flexible definition (Cinbis and Aksoy, 2007) that entails higher intuition and can describe more subjective aspects.

The fuzzy distance relations has gained more recognition, as it can be found one the literature. According to Bloch (1999), there are two main categories in this type of fuzzy relation: distances that incorporate only membership functions and compare these memberships point-wise, and distances that include spatial distances in addition. These definitions allow for a broader analysis of the composition and structure of images, for applications where structural topological and spatial relationships are of utmost importance. These distances achieve two goals in that they combine the membership values at different points in space S, while including in the calculation their proximity to S. The advantage of this approach is that distances are expressed algebraically and retain their properties, making them easier to translate to fuzzy cases.

In the following paragraphs are presented the main approaches and algorithms that have attracted the majority of research focus in the direction of modeling fuzzy spatial relations. The following frameworks have been designed in a way that they incorporate calculations point – point, point – object, crisp object – crisp object and fuzzy object – fuzzy object.

Aggregation of Angles: The basis of this approach as was stated by Krishnapuram *et al*. (1993) is the angular information between the two objects. Specifically the two objects are considered as fuzzy regions and the their properties as well as their relations between them are viewed as membership functions which are defined over the set of a-cut sets of the fuzzy regions.

Compatibility assessment method: This method, which was introduced by Miyajima and Ralescu (1994), also known as Histogram of Angles, is based also on the angular information between two points as the previous one with the difference that the positive angles are calculated clockwise. Then the membership function of the spatial relation between these two points is derived by a trigonometric function.

Centroid method: As proposed by Keller and Wang (2000), this method is based on the computation of the centroids and following to that the fuzzy membership of the spatial relations is calculated, with respect the angular measurement of the centroids, using the same functions as in the aggregation method. A characteristic example in this category can be found on the work of Gudivada and Raghavan (1995) where the used the angles of the object centroids to define similarity based on directions.

Projection and Dominance Method: Keller and Sztandera (1990) initially proposed this method, which is based on the a-level sets of the fuzzy sets' projections onto two orthogonal principal axes. Following to that, a partial membership is computed based on a new dominance relation for each axis and then the final fuzzy set is derived by the combination of the partial memberships. A characteristic example in this category comes form the work of Nabil *et al.* (1996) where they proposed a projection-based method using conceptual neighborhoods to compute relation similarity.

Fuzzy Morphology: This method initially proposed by Rosenfeld (1979) where he introduced topology in fuzzy sets but was further researched and improved by Bloch and Maître (1995) and especially in the direction of spatial relations. According to them, the proposed methodology based on mathematical morphology to describe the fuzzy distances incorporating the spatial information by using the present strong links between mathematical morphologies (i.e. dilation) and distances.

R-Histogram: This method was initially introduced by Wang and Makedon (2003), which extended the idea of Histogram of Angles as a quantitative method for the definition of directional relations between crisp objects. Later on, Wang *et al.* (2004) further improved this method in order to incorporate the calculation of arbitrary topology among objects.

Histogram of Forces: This method was initially proposed by Matsakis and Wendling (1999) and consists of an idea that is different from the previous aggregation and histogram methods due to the fact that these ones were based primarily on point-to-point relations therefore they define objects as sets of points while this method incorporates crisp and fuzzy objects as *longitudinal sections*. A more analytical explanation of Histogram of Forces is given in the following chapter since is considered one of the building blocks of our proposed framework for the semantic similarity of spatial scenes.

CHAPTER 3: PROPOSED FRAMEWORK

In this chapter it is proposed a framework for the development of sufficient metrics in order to appropriately describe the spatial context of a scene so as to create a spatial configuration signature. An ontology-driven approach (Section 3.1) based on the creation of spatial signatures in the component objects level, and the use of the Histogram of Forces of fuzzy Allen relationships are devised (Sections 3.2-3.4). In Section 3.5 a data mining procedure is applied in order to reduce the dimensionality and keep only the essential relationships that maximize the similarity scores. The similarity method applied on the derived histograms based on the use of a generalized Normalized Cross Correlation as it is explained along with the overall framework in Section 3.6.

3.1 The Approach

The approach was designed in a way that will be able to be applicable in two different test cases in terms of type of geospatial data and their sources. Therefore in this chapter is presented the theoretical foundation as well as the explanation of the proposed framework and methodology, which justifies its selection and its applicability. The analytic presentations of the two datasets as well as the application of the similarity framework and its results for the two different test cases are presented in Chapters 4 & 5.

We consider that a scene can be described by a prototypical ontology, which is comprised of a set of objects / key features that define this prototype. The terms object and feature are used interchangeably in the content of the present work. The scene similarity is mainly based on the *spatial signature* that characterizes the prototypical ontology and the comparison is based on matching *spatial signatures* between the prototypical ontology of a scene and the new unknown scenes. For the purposes of developing the appropriate similarity measure, Histogram of Forces coupled with fuzzy Allen relations have been implemented. Figure 3.1 illustrates a generic representation of the scene matching based on the Histograms of Forces coupled with fuzzy Allen relations. The analytical explanation of the proposed methods as well as its implementations will be discussed in the following subchapters.

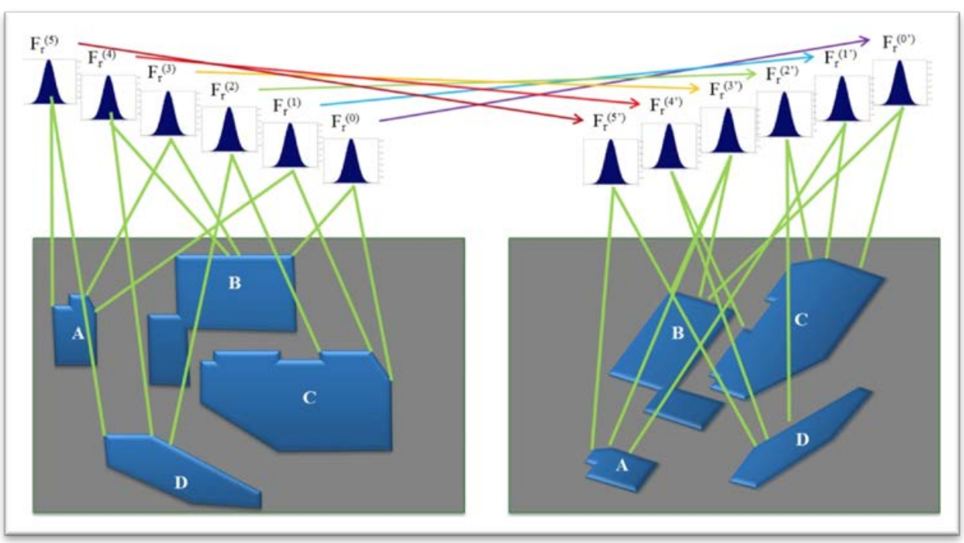

Figure 3.1: Scene similarity/matching based on the Histograms of Forces coupled with fuzzy Allen relations for pairwise combinations.

3.2 Allen Relations

The adapted model for the representation of spatial relations is Allen's Interval

Algebra, which was primarily applied on the temporal domain and mainly used in the field of AI (Allen, 1983). According to Allen's Algebra, there are thirteen interval relations mutually exclusive and exhaustive: before, meets, overlaps, during, starts, finishes, their corresponding converse, and equal. Those relations can be applied on space by decomposing a 2D object into 1D parallel segments. In Table 3.1 the thirteen base relations used in Allen's interval algebra are illustrated. The entire algebra also known as *Allen's interval algebra* is comprised of 2^{13} possible disjunctions of these base relations and has an NP-complete consistency problem (Vilain and Kautz, 1986).

Table 3.1: The thirteen base relations of Allen's interval algebra.

Interval Base Relation	Symbol	Pictorial Example	Endpoint Relations
x* before *y	$\prec$	xxx	$X^- < Y^-$, $X^- < Y^+$,
y* after *x	$\succ$		
		yyy	$X^+ < Y^-$, $X^+ < Y^+$
x* meets *y	m	xxxx	$X^- < Y^-$, $X^- < Y^+$,
y* met by *x	$m^{\smile}$		
		yyyy	$X^+ = Y^-$, $X^+ < Y^+$
x* overlaps *y	o	xxxx	$X^- < Y^-$, $X^- < Y^+$,
y* overlapped by *x	$o^{\smile}$		
		yyyy	$X^+ > Y^-$, $X^+ < Y^+$
x* during *y	d	xxx	$X^- > Y^-$, $X^- < Y^+$,
y* includes *x	$d^{\smile}$		
		yyyyyyyyyy	$X^+ > Y^-$, $X^+ < Y^+$
x* starts *y	s	xxx	$X^- = Y^-$, $X^- < Y^+$,
y* started by *x	$s^{\smile}$		
		yyyyyyyyyy	$X^+ > Y^-$, $X^+ < Y^+$
x* finishes *y	f	xxx	$X^- > Y^-$, $X^- < Y^+$,
y* finished by *x	$f^{\smile}$		
		yyyyyyyyyy	$X^+ > Y^-$, $X^+ = Y^+$
x* equals *y	$\equiv$	xxxx	$X^- = Y^-$, $X^- < Y^+$,
		yyyy	$X^+ > Y^-$, $X^+ = Y^+$

According to this kind of algebra are described all the possible relations between two convex intervals. Every interval can be represented using the two end points of the interval as illustrated on the above table. When comparing the end points of two intervals according to the relations of the point algebra, two intervals can be related by the 13 different JEPD base relations.

Although Allen relations was initially invented for temporal reasoning in AI ever since 1983 when this seminal work was presented, these composition tables (also known as transitivity tables), the constructions of such tables have became a major challenge for the current QSR approaches (Ranfell *et al*., 1992). This argument was also supported by Guesgen, (2002) which as he stated, Allen's logic is also applicable in spatial reasoning by interpreting the 13 Allen relations as spatial relations between objects. By applying Allen's methodology on spatial relations it enables us to create an instrument to reason about space. An important work to this direction have been accomplished by El-Geresy and Abdelmoty (2004) where they presented a qualitative spatial reasoning engine for deriving automatically composition tables among various types of objects according to the space division theory inside the 9IM.

This kind of spatial representation is very suitable for the present application of the ontology classification based on the spatial attributes of the objects for a number of reasons. Primarily, due to the homeomorphism between Allen's temporal relations and the 1D topological relations in the spatial domain, these relations are able to extract combined topological and directional information as described later in the dissertation. In addition, they divide the space in thirteen partitions as shown in Figure 3.2; each one for every relation, and the decomposition process is repeated in every direction, supporting the topological and directional information.

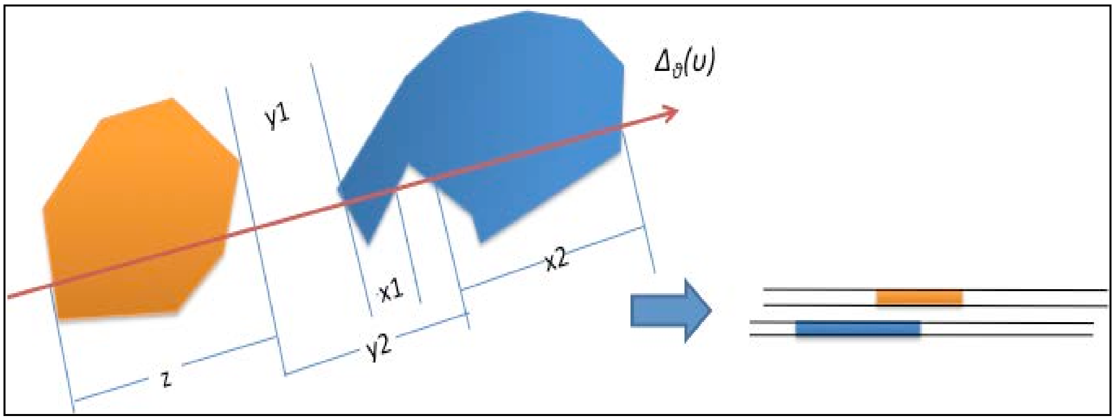

Figure 3.2: Example of space decomposition in partitions according to Allen's interval algebra.

3.3 Histogram of Forces

Histogram of Forces (HoF) also known as *F-histograms* initially was introduced by Matsakis and Wendling, (1999) based on the idea that acceptable representations of relative position can be acquired by the deducing the handling of all the 2D and 3D objects to the handling of 1D entities. While this idea evolved with time, proposing further improvements, its basis relies on a concrete mathematical foundation for the evaluation of spatial relations between pairs of 2D objects, offering solid theoretical guarantees and nice geometric properties. It can be applied to raster as well as vector data and also it is very a robust method for handling fuzzy objects, as well as crisp objects, intersecting objects, disjoint objects, and unbounded objects, and bounded objects. Its fundamental framework permits the calculation of multiple spatial representations such as the histograms of constant and gravitational forces. The first category of HoF offers a global perspective similarly to the histogram of angles, while the second one assigns more emphasis to the objects' regions that are close and/or facing to each other.

Consider two 2D objects A and B. The forces acting between them can represent the spatial relation between these two objects. For every direction θ, the sum of elementary forces acting between those two objects is calculated in the direction θ (Figures 3.3 & 3.4). F-histogram $F_r^{AB}(\theta)$ is the aggregation of these forces that maps $\mathbb{R} \rightarrow \mathbb{R}^+$ and resembles the degree of support for the proposition, "A is in direction θ of B". The magnitude of each of the forces is computed as an inverse ratio of d^r, where d is the distance between the points contained in objects A and B, and *r* regulates modes for capturing different information. For instance when r = 0, the histogram of constant forces (F_0) is computed, which delivers a global perspective without incorporating the distance between A and B. When r = 2, the histogram of gravitational forces (F_2) is computed, which delivers a local view that is more sensitive to nearby points but independent of the global scale, which means that HoF are also sensitive to distances between the objects.

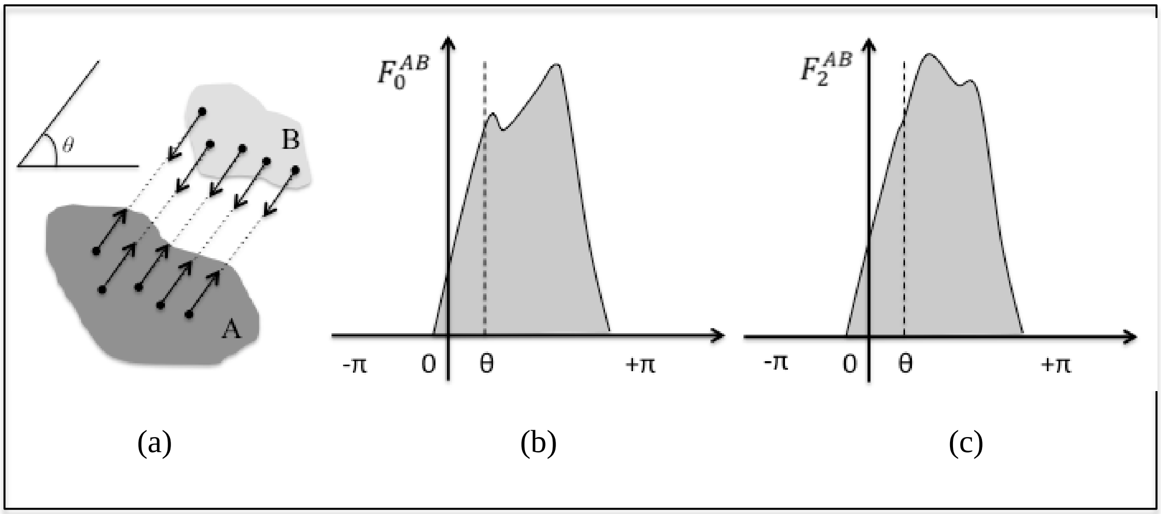

Figure 3.3: Calculation of histogram of forces. (a) Histogram of force $F_r^{AB}(\theta)$ is the resulting scalar of elementary forces which are extending from the points of A to those of B in the direction θ. (b) A spatial representation between A and B in the case of histogram of constant forces (r = 0). (c) A spatial representation between A and B in the case of histogram of gravitational forces (r = 2).

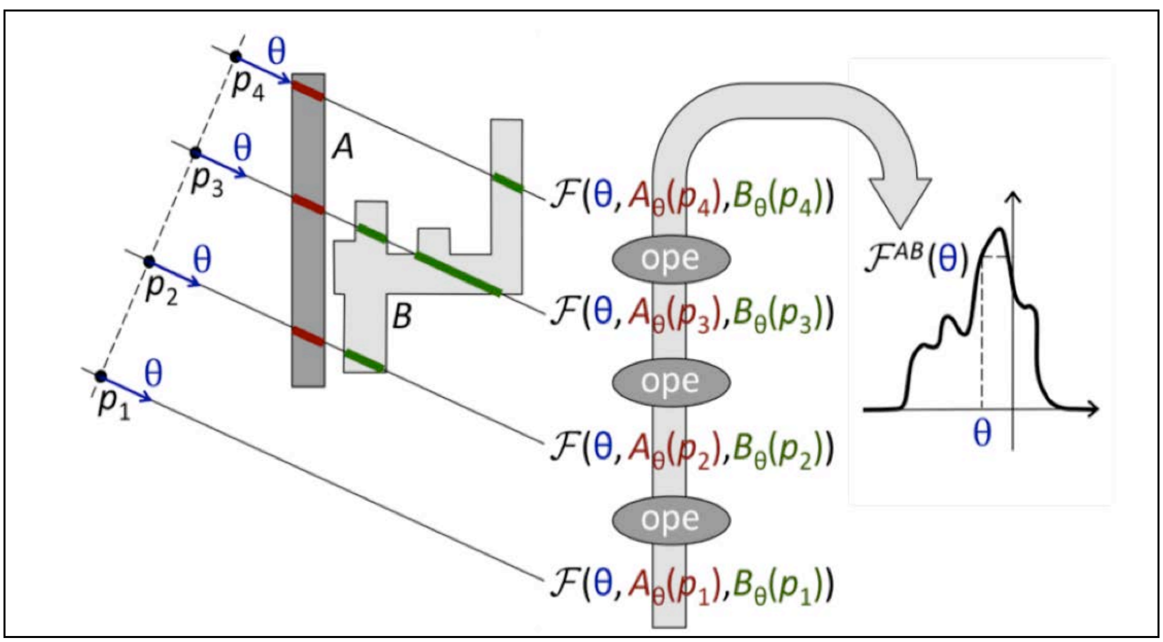

Figure 3.4: Principle of the calculation of the histogram of forces $F^{AB}(\theta)$ (adapted from Matsakis *et al*., 2010).

Beyond the fact that HoF are an extremely suitable method for handling the majority of possible representations of objects/features, they also provides other significant benefits, which are essential for the purpose of scene similarity task. According to Matsakis *et al*. (2004), HoFs are relative position descriptors with high discriminative power. A great advantage that they introduce is the fact that they achieve invariance in affine transformations such as commutativity, orthogonal symmetry, central dilation (scale), stretch, translation and rotation as shown in Figure 3.5. Likewise, any two of the following elements, 1) an affine transformation, 2) a relative position (via HoF), and 3) the "transformed" relative position, allow the third one to be recovered. This becomes very critical in scene matching where invariance to various transformations is one of the key challenges (Stefanidis *et al*., 2002).

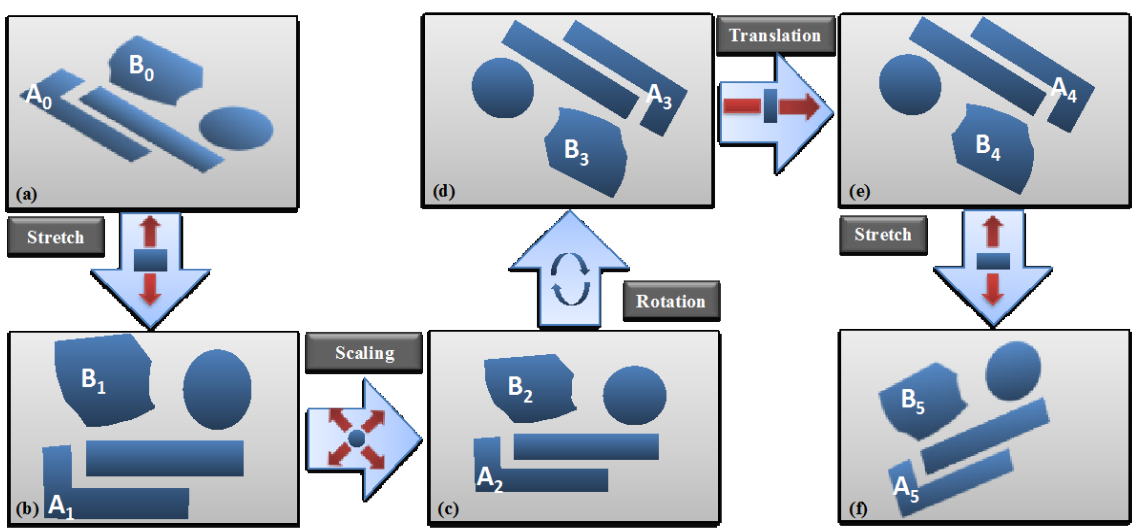

Figure 3.5: Affine properties of HoF. Given two objects A and B, HoF present invariance to affine transformations and manage to preserve the similarity between these two objects (i.e. (A_0 , B_0) matches to (A_5 , B_5)).

Another important advantage of HoF which is very suitable for the design of our prototype is the fact that they present great fexibility on modeling of fuzzy spatial relations (Matsakis *et al.*, 1999). There are three main methods that are most common in the literature to achieve this; the aggregations method (Krishnapuram *et al.*, 1993), the compatibility method (Miyajima and Ralescu, 1994), and the method based on force categorization (Matsakis *et al.*, 2001). The fuzzy relations satisfy four fundamental properties wich form the axiomatic basis where the concept of HoF was built upon: in the case where objects are adequitely far apart, then each one can be seen as a single point in space; the directional relationships are insensitive to scale changes; the semantic inverse principle (Freeman, 1975) is preserved (i.e. object *A* is to the left of object *B* as much as *B* is to the right of *A*); all directions have the same importance. These properties enable the determination of how the fuzzy relations respond when the objects are similarity-transformed (Matsakis *et al.*, 2010). Although HoF were initially designed as relative position descriptors based primarily on directional information, they are able to incorporate other types of spatial relations equally successfully as it will be explained in the following subchapter.

3.4 Fuzzy Allen Relations Coupled With HoF

There are various approaches that can be used for the fazzification of Allen relations. The majority of them use fuzzification based on the human defined variables, primarily for use in temporal domain for the qualitative aspects of temporal knowledge and reasoning processes (Schockaert *et al*., 2008). As was already mentioned though, fuzzy Allen relations gained high applicability in the spatial domain also, being able to model all the types of spatial relations where vagueness and/or fuzziness are represented at the relation's level.

For the purposes of a complete ontology driven scene similarity in the context of QSR, what was considered important was to combine all the aspects of spatial relations according to a fuzzy approach. Despite the fact that the pre-existing models such as the RCC and the 9IM have already been extended so as to incorporate the fuzziness (Palshikar, 2004; Shi and Liu, 2007), they are still having some limitations. In general, the majority of the existing fuzzy relations applicable only for disjoint topological relations. Concerning specifically the RCC and the 9IM, although they have rich topological information are lacking of the directional component. For these reasons, for the relation's representation method proposed by Matsakis and Nikitenko (2005) found to be very valuable. According to this approach the authors are utilize a fuzzy version of Allen's interval algebra to extend F-histogram to the incorporation of representation of topological relations too (Allen, 1983). The fuzzified Allen's relations are given by the following equations (Equation 5) while the graphical representation of them is illustrated in Figures 3.6 and 3.7.

Equation 5: The fuzzified Allen's relations.

$$\left.\begin{aligned}
&f_{<}(I,J) = \mu_{\left(-\infty,-\infty,-b-\frac{3\alpha}{2},-b-\alpha\right)}(y)\\
&f_{>}(I,J) = \mu_{\left(0,\frac{a}{2},\infty,\infty\right)}(y)\\
&f_{m}(I,J) = \mu_{\left(-\beta,-\frac{3\alpha}{2},-\beta-\alpha,-\beta-\alpha,-\beta-\frac{\alpha}{2}\right)}(y)\\
&f_{mi}(I,J) = \mu_{\left(-\frac{a}{2,0,0},\frac{a}{2}\right)}(y)\\
&f_{o}(I,J) = \mu_{\left(-b-a,-b-\frac{a}{2},-b-\frac{a}{2},-b\right)}(y)\\
&f_{oi}(I,J) = \mu_{\left(-a,-\frac{a}{2},-\frac{a}{2,0}\right)}(y)\\
&f_{f}(I,J) = \min(\mu_{\left(-\frac{b+a}{2},-a,-a,+\infty\right)}(y),\mu_{\left(-\frac{3\alpha}{2},-\alpha,-\alpha,-\frac{\alpha}{2}\right)}(y),\mu_{\left(-\infty,-\infty,\frac{z}{2},z\right)}(x))\\
&f_{fi}(I,J) = \min(\mu_{\left(-b-\frac{a}{2},' ab' b,' b+a/2\right)}(y),\mu_{(-\infty,-\infty,-b,-(b+a)/2)}(y),\mu_{(z,2z,+\infty,+\infty)}(x))\\
&f_{s}(I,J) = \min(\mu_{\left(-b-\frac{a}{2},' ab' b,' b+a/2\right)}(y),\mu_{(-\infty,-\infty,-b,-(b+a)/2)}(y),\mu_{(-\infty,-\infty,z/2,z)}(x))\\
&f_{si}(I,J) = \min(\mu_{\left(-\frac{b+a}{2},-a,-a,+\infty\right)}(y),\mu_{\left(-\frac{3a}{2},-a,-a,-a/2\right)}(y),\mu_{(z,2z,+\infty,+\infty)}(x))\\
&f_{d}(I,J) = \min(\mu_{\left(-b,-b+\frac{a}{2},-\frac{3a}{2},-a\right)}(y),\mu_{(-\infty,-\infty,z/2,z)}(y))\\
&f_{di}(I,J) = \min(\mu_{\left(-b,,-b+\frac{a}{2},-\frac{3a}{2},-a)\right)}(y),\mu_{\left(\frac{z}{2},z,+\infty,+\infty\right)}(y))
\end{aligned}\right\} \quad (5)$$

where $a = min(x,z)$, $b = max(x,z)$, x is the length of segment (I) of argument object A, z is the length of segment (J) of reference object B and x, y, z are the line segments of the two objects. The majority of the relations can be defined by single membership function and some of them by minimum of multiple membership functions such as d(*during*), d_i(*during by*), f (*finish*), f_i (*finished by*). When the fuzzy Allen relations are shared between them then these two relations are directly neighbors. If $0 < r_1(I,J) < 1$ then 0 <

$r_2(I,J) < 1$ such that $r_1(I,J) + r_2(I,J) = 1$ and $r_1(I,J)$, $r_2(I,J)$ are neighbors. This indicates that the sum of all the Allen relations is always one.

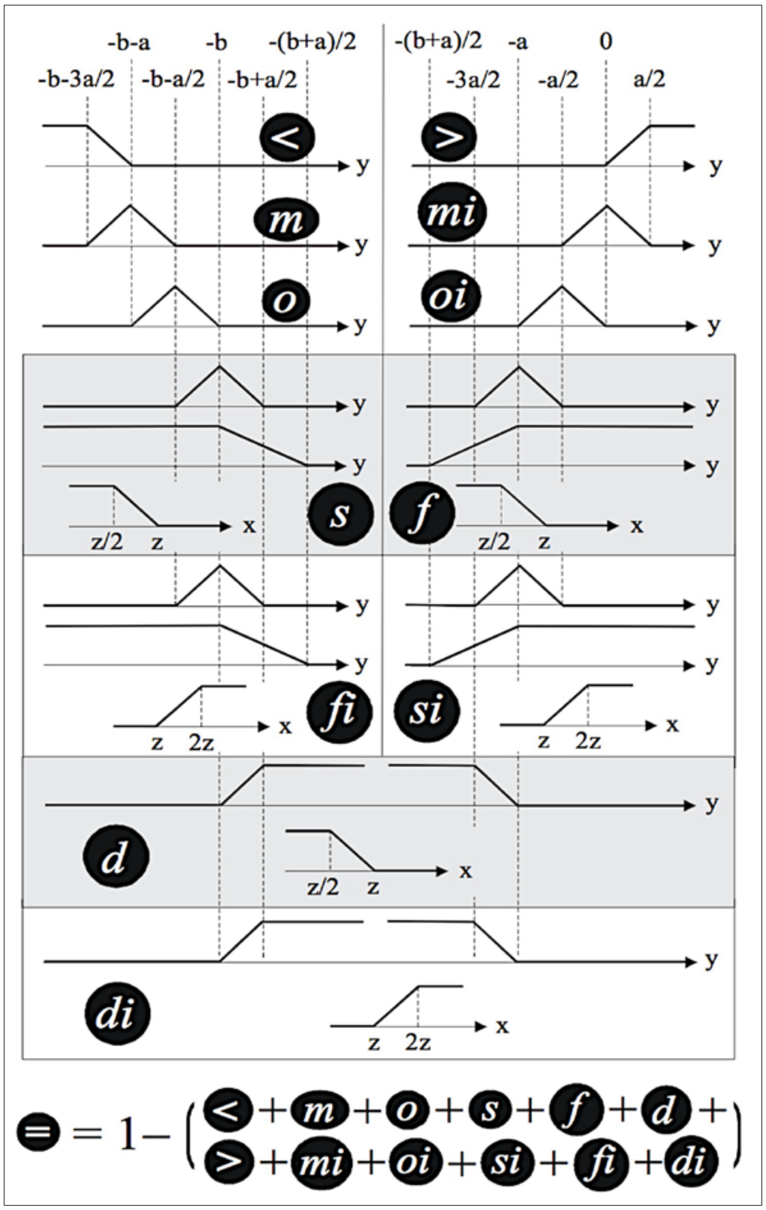

Figure 3.6: The 13 fuzzified Allen relations between two segments I and J on an oriented line x is the length of I (the argument), z is the length of J (the referent), a is min(x,z), b is max(x,z), and y is the relative position of I to J (adapted from Matsakis and Nikitenko, 2005).

According to that model, the thirteen interval relations mutually exclusive and exhaustive as they described on previous subchapter are: < (before), m (meets), o (overlaps), d (during), s (starts), f (finishes), and their corresponding converse > (after), mi (met by), oi (overlapped by), di (contains), si (started by), fi (finished by), and = (equal) that can be applied in space to decompose a 2D object into 1D parallel segments.

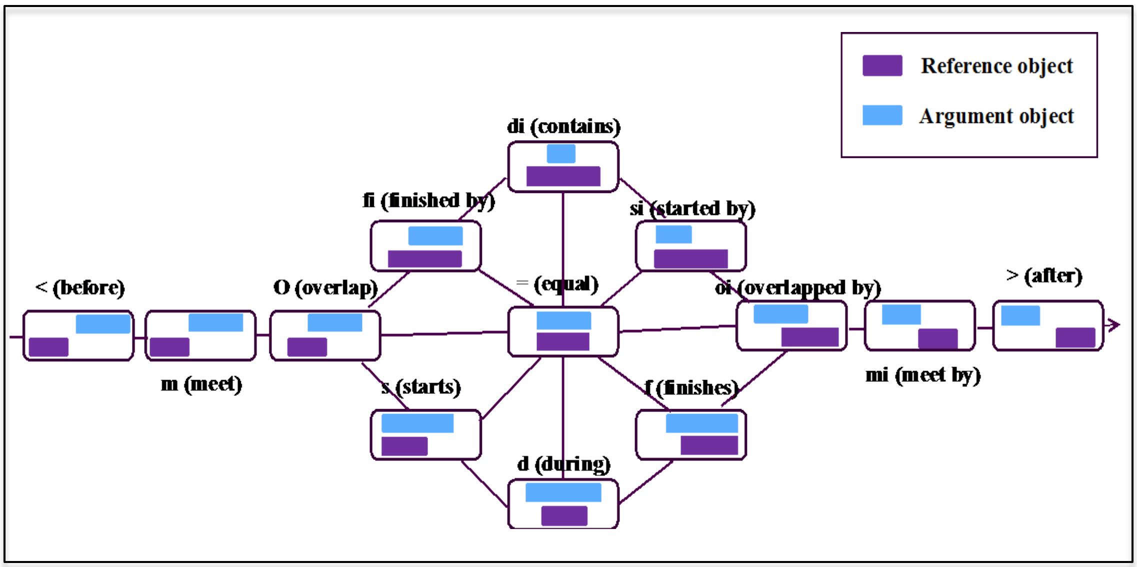

Figure 3.7: Graphical representation of the 13 Allen's spatial relations between segments of a pair of objects, the reference and the argument.

For the representation of the relations, we have selected the HoF, which provides the relative position of a pair of 2D objects (Figure 3.8). Due to the homeomorphism between Allen's temporal relations and the 1D topological relations in the spatial domain, these relations are able to extract combined topological and directional information. The HoF attaches a value to the argument object A that lies in a specific relation B in direction θ, and it is defined as, *Equation 6: The Histogram of Forces between two objects.*

$$F^{AB}(\theta) = \int_{-\infty}^{+\infty} F(\theta, A_\theta(v), B(v)dv \quad (6)$$

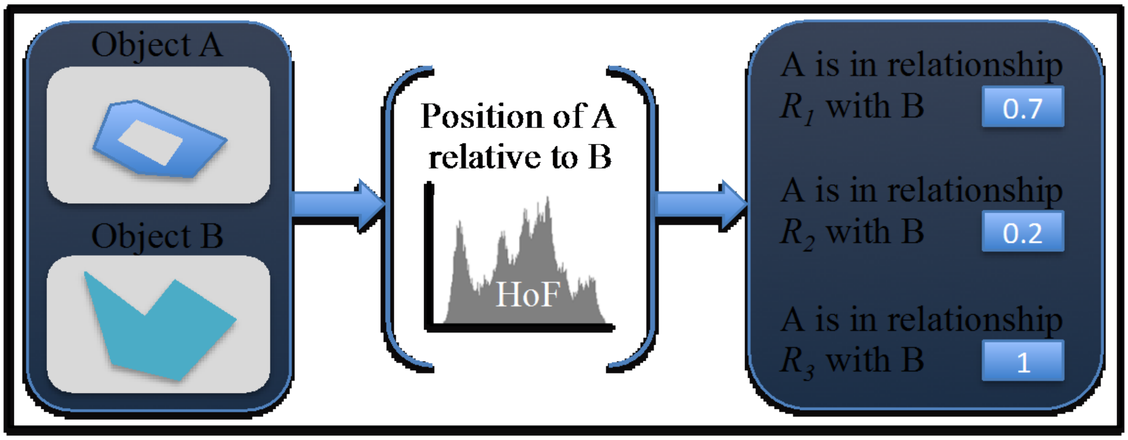

Figure 3.8: The positioning of two objects, position of argument object A relative to reference object B based on HoF. On the right side the relation R1 has the the highest fuzzy logic value and so is the correct one.

One of the most critical steps for the fuzzy representation of the relations is the correct choice of membership function according to the given application. A commonly used trapezoidal membership function is presented with Equation 7.

Equation 7: Trapezoidal fuzzy membership function.

$$\mu_{(\alpha,\beta,\gamma,\delta)}(u) = \max(\min\left(\frac{u-a}{\beta-\alpha}, 1, \frac{\delta-\alpha}{\delta-\gamma}\right), \quad (7)$$

where μ is the function in a set X (μ : X) →[0,1] and u,α,β,γ,δ ∈ R ∧ α < β ≤ γ < δ. For the specific case of the given study, a polygonal membership function was utilized for the treatment of the longitudinal sections, which was proposed by Salamat and Zahzah (2012). Specifically the calculation and extraction of the component objects of each ontology's feature class in a pairwise fashion. For instance, given an ontology with a feature class comprised of five objects A, B, C, D, and E, according to equation 8, ten unique pairs of objects have been derived such as [AB, AC, AD, AE, BC, BD, BE, CD, CE, DE].

Equation 8: k-combination of a set S.

$$\frac{n!}{((n-k)!k!)} \tag{8}$$

where n is the number of objects and k is the number objects under to be compared (k =2 for pairwise calculations).

Given two objects A and B the calculation of the HoF begins with the computation of the contours and edges of both objects. The algorithm begins with a fix angle and lines passing via the vertices of the two polygons that are drawn. Then the intersected line with a boundary is calculated and then the projections of these points create the line segment. Furthermore, the fuzzy Allen relations are calculated with the use of fuzzy logic connectors. This process is repeated for the remaining twelve segments, and all the relations are summed and multiplied by the total surface areas of the objects between the given line segment. Finally, the angle is increased by one degree and the aforementioned procedure is repeated in the range 0^{o}– 360^{o}. The resulting histogram of fuzzy Allen relations is a representation of the total area of the part of object A that faces the part of object B in a predefined direction θ, under a specific relation. All this information has been stored in matrices of dimension 13x360 (13 relations, 360^{o}), containing actual values that represent topology direction and also distance. This is very essential for the purposes of scene similarity which has to be based in comparable quantitative measurements and will enable a meaningful and accurate comparison using a Normalized Cross Correlation between HoFs, as it is explained in the following subchapter.

3.5 Optimal Attribute Selection

Before the application of the similarity procedure, an important step is to reduce the dimensionality of the extracted relations in order to compare the scenes based only on the most optimal relations and so to increase the overall scores. Therefore it is important to select only the relevant relations that purely characterize each ontology category and eliminate form the similarity procedure the irrelevant ones. In the data mining literature that issue also referred as "curse of dimensionality" (Hastie *et al.*, 2009), which is a major problem that directly affects the success of data mining algorithms due to the increase of the *sparsity*. In order to cope with that issue, the solution can be found on one of the most essential components of data mining and machine learning, called *attribute subset selection*. In our case the word attribute refers to the spatial relations that have been used which are thirteen in total. Another important motivation for this optimal selection was to further reduce the variance caused by high differences on the attributes of the scenes, contributing that way in a higher invariance in overall.

For the attribute selection process the input that is used is the extracted relations from the training scenes. That selection was based on the fact that the training data are able to provide more information in order to determine which attributes are most optimal. Hence we utilize only the most essential ones in order to maximize the similarity results and classify with higher accuracy each of the test airport ontologies to the correct category. For the implementation, Weka v3.6.8 has been used which is open source software with a very complete inventory of algorithms for the majority of machine learning applications (Hall *et al.*, 2009). The overall subset selection scheme was based on a wrapper approach where a data-mining algorithm is applied in order to find the best possible attributes subset. The selection is based on two major components; the evaluator algorithm, which determines the merit of single attributes or subsets of attributes and the search algorithm, which is the search heuristic. More specifically for the attribute evaluator the Classifier Subset Evaluator has been used where the classification scheme selected to be the NBTrees (Kohavi, 1996). NBTree is a hybrid between decision trees and Naïve Bayes classifiers that creates trees in which every leaf is a Naïve Bayes classifier for the instances that reach the leaf (Witten and Frank, 2005). For the search algorithm, the Best-first was used (Dechter and Pearl, 1985), which is a graph-based heuristic search algorithm that searches the feature space based on a greedy hill-climbing optimization technique. The evaluation applied at the training data set for each of the ontology categories separately.

3.6 Scene Similarity Framework

The main idea in which the entire methodology is based on is to create a spatial signature for each prototypical ontology in the component objects level and by using the HoF of fuzzy Allen relationships to develop a similarity method applied on the derived histograms of the same objects in each scene. The similarity was based on the use of a generalized Normalized Cross Correlation (NCC) between the matrices that are generated from the Histograms of Forces.

NCC has been traditionally used in digital image processing for applications such as image registration, template matching and histogram matching in general. It was selected as a similarity measure due to its robustness as also due to its suitability to the specific application. One of the main advantages of the NCC is that is invariant to Y axis which represents the area of pixels while the X axis remains constant for all the histograms. On the other side a drawback is that the typical NCC is applicable only between matrices of different size such as for example the image matrix and the template matrix that is always of smaller size (Lewis, 1995). In order to overcome this we adopted a generalized NCC proposed by Padfield *et al*. (2011), which provides the flexibility of comparing matrices of the same size. Specifically, as it was mentioned, HoF was translated into matrices that contain the values of each of the 13 relationships between an object pair, in the direction 0^o – 360^o. At this level the NCC is applied between every object pair of the test data set ontologies and the training data set ontologies. For instance, given 10 unique object combinations for each ontology (objects: A, B, C, D, and E), we calculate for each pair of the training data with the corresponding of the test data. For example, for the extracted relations between an object A and an object B, the calculation will be such as:

$$NCC_1\ (AB_{test}, AB_{training\_1}) \ldots NCC\ (DE_{test}, DE_{training\_1})$$

$$NCC_n\ (AB_{test}, AB_{training\_2}) \ldots NCC\ (DE_{test}, DE_{training\_2}).$$

After finding the correlation coefficient (0 – 1) for every corresponding object pair between the tested ontologies and all the other training ontologies of the same category then we calculate the average value of all the correlation coefficients and the similarity score is derived. Figure 3.9 illustrates the main framework flowchart that was designed for the implementation of the scene similarity task. The algorithmic implementation of the similarity algorithm of HoF coupled with fuzzy Allen relations as well as the matching assessment was developed in Matlab.

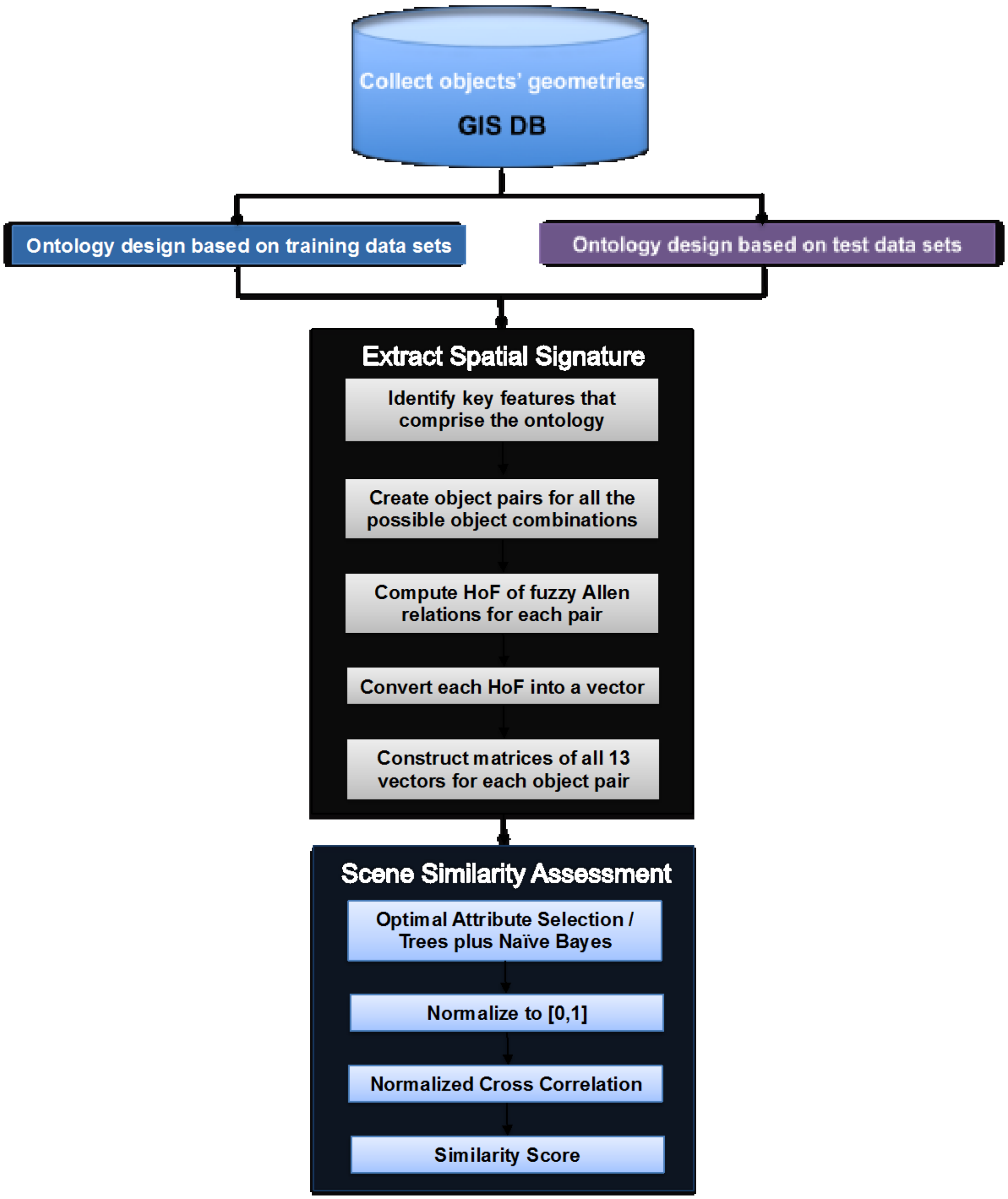

Figure 3.9: Main framework flowchart for the implementation of the scene similarity task

CHAPTER 4: COMPOSITE SCENES IN BUILT ENVIRONMENTS

In this chapter it is presented the application of the proposed methodology described in Chapter 3. This is the first test case whereby the study is comprised of composite scenes in the built environment. In this test case we consider as *built scenes* the spatial scenes that consist of manmade structures. Specifically the first test case addresses structured built environments in satellite imagery, using airport compounds and how the proposed semantic similarity can overcome the local dependences and differences of each airport scene and provide us with comparable results. In Section 4.2 the study area and data that was utilized are presented while in Section 4.3 is presented the scene model of this test case. Section 4.4 concludes with the similarity results.

4.1 Introduction

In the present study we consider that composite objects comprise components of a spatial scene. Therefore spatial scenes can be represented as a composite of geographic information constructs which they convey a higher level information by encupsulating the interelations between the functionality, internal structure and usage of these scenes. Given the fact that an ontology manages to identify and model the concepts and their relationships between the objects comprising a scene, it enables a higher scene understanding and/or description of the image content by linking also the contextual information in semantics level. The spatial arrangement of these components often implies usage and as such may be adequate to differentiate sub-classes. More specifically in our test case the compisite objects are considered the fundamental functional components, which comprise the ontology “airport”, as they are described via the spatial content of the satellite imagery. Based on the feature class of the aforementionent components that describes the ontology we calculate the spatial signature, in pairwise fashion, enabling this way a comparison between the prototypical/known ontologies and the uknown ones.

4.2 Study Area and Data

The dataset was comprised of fourty airport scenes that have been acquired by Digital Globe commercial imaging satellite WorldView-2 that were used as the main dataset for the collection of the feature class objects geometry. More specifically, the data used were the panchromatic images, level 2a, of .46m GSD at nadir, acquired in the period of 12/2010 – 7/2012. The study area was focused on the African continent. Figure 4.1 illustrates the distribution of the all the airport locations accros the continent while Table 4.1 presents the twenty six airports that were used for our analysis since the remaining fourteen scenes have been considered unsaficied due to their lack of basic components.

Figure 4.3: Distribution of the all the airport locations accros the continent.

Table 4.1: Airport scenes that have been used for our study.

Civilian		Military		Joint	
Airport	Country	Airport	Country	Airport	Country
Badala	Guinea	Antananarivo	Magadascar	Aba Tenna Dejazmatch	Ehiopia
Dodoma	Tanzania	Bole	Ethiopia	Abeche	Chad
Dongola	Sudan	Gweru Thombill	Sudan	Brazzaville	Congo
Kikwit	Congo	Kamina	Congo	Dirkou	Niger
Kisumu	Kenya	Makurdi	Nigeria	Jomo Kenyatta	Kenya
Maiduguri	Nigeria	Monrovia Spriggs	Liberia	Kaduna	Nigeria
Nouakschott	Mauritania	Ngerengere	Tanzania	Lusaka	Zambia
Old Aba Segud	Ethiopia	Thebephatshwa Maparangwane	Botswana	Ougagadougou	Burkina Faso
Windhoek Hosea Kutako	Namibia	-	-	Yaounde	Cameroon
Total: 9		Total: 8		Total: 9	

The main reason behind incorporating data from an entire continent was to provoke a more challenging scene-matching task since every region, in country or even state level, presents variances at the size and the shape of the airports' basic components as well as at their spatial distribution. For instance, the spatial characteristics of an international airport in a capital city, which usually is very well structured, will significantly different from a less structured airport or primitive in a rural or even in a dessert area where sometimes just a house serves as a terminal. A visual example of this argument is illustrated in the Figure 4.2 where Dirkou airport located in the desert area of Nigeria is contrasted with Jomo Kenyatta International Airport, which is the main international airport serving the capital of and largest city, Nairobi in Kenya.

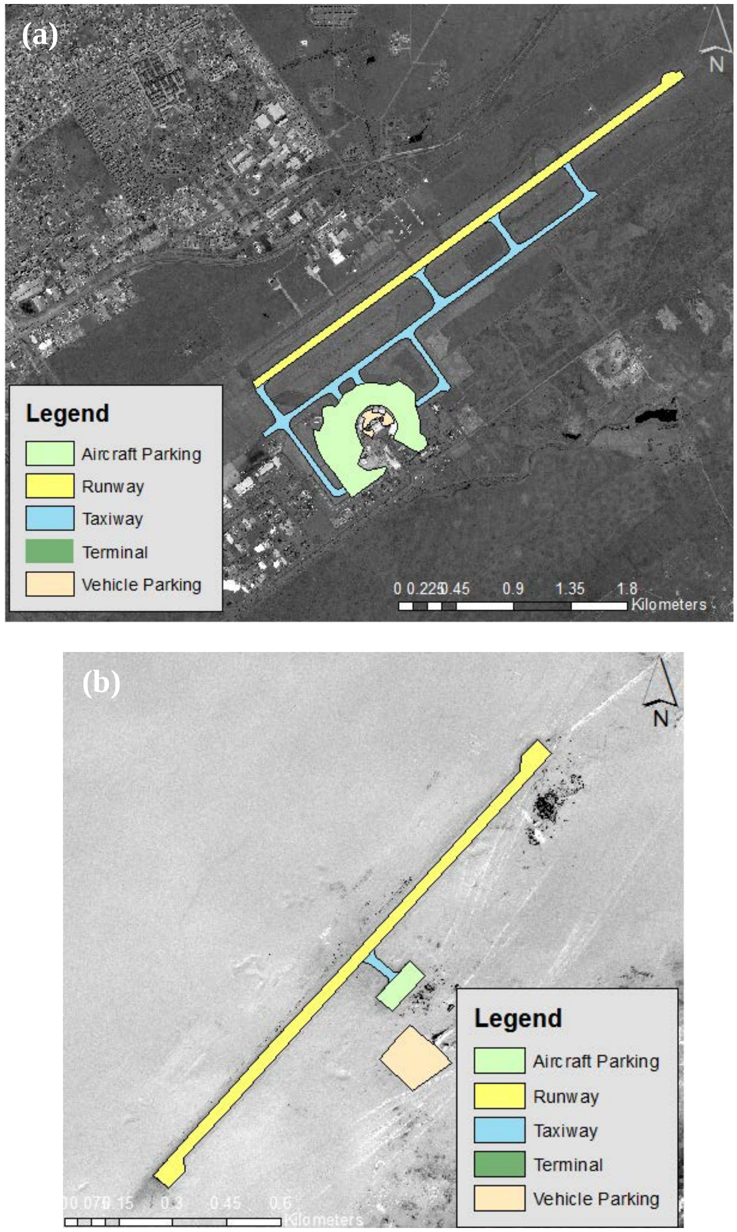

Figure 4.2: Infrastructural differences between varius airports. (a) Jomo Kenyatta International Airport of Nairobi in Kenya. (b) Dirkou Airport in Kenya.

As it becomes apparent by the two airports in Figure 4.2, a scene-similarity procedure based on metric information and consequently in the shape and the size of the constituted components of the airports, will not provide as with sufficient results since they vary according to the functionality and the purpose of each airport. That becomes especially critical when we need to compare airports from different countries in global level where their infrastructural standards as well as their specifications diverse.

4.3 The Scene Model

In order to overcome the aforementioned limitations we consider that a scene can be described by a prototypical ontology, which is comprised of a set of objects / key features that define this prototype as it was described in the previous chapters. For the test case of the built scenes the scene similarity is mainly based on the *spatial signature* that characterizes the prototypical ontology and the comparison is based on matching *spatial signatures* between the prototypical ontology of a scene and the new unknown scenes. More specifically, based on Table 4.1, three major airport categories have been distinguished based on the usage type, named as “Civilian”, “Joint”, “Military”, consisting of nine airports scenes in the first type, eight in the second, and three in the third type.

Five component objects have been selected for the description of the feature classes of the ontology “airport”. These components were selected in order to be the most descriptive as well as common to all the scenes: the runway (component A), the taxiway (component B), the terminal (component C), the vehicle parking (component D) and the aircraft parking (component E) . In cases where an component object type was more than one, for example in the case of taxiways, only the major ones have been selected. Figure 4.3 illustrates an example of the airport ontology’s main components. By identifying these key components of the airfield class ontology, we formulate the framework for deciding the appropriate qualitative measurements for use in the determinations of similarity.

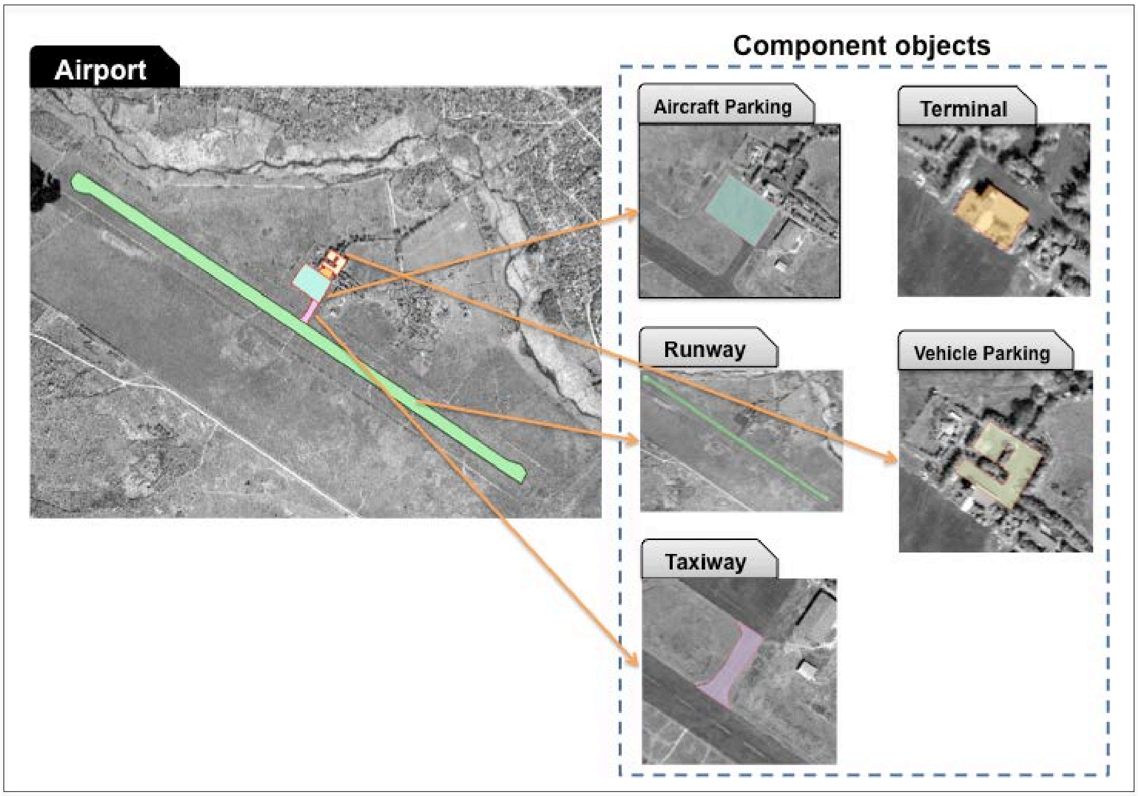

Figure 4.3: Component objects of civilian feature class, Aba Segud airport in Ethiopia.

4.4 Experiments and Results

Initially, the collection of the geometries for the airfield components was implemented using ArcGIS by manually digitizing geometries based on visual interpretation of the very well defined features, since the need for automatic feature detection was out of the scope of this study. For the purpose of the scene similarity, since the given data was used as training set, a set of synthetic airports was created based on the summary statistics of the known airports in order to check the similarity application. Specifically, twenty synthetic airports have been created for each of the three ontology categories. Consequently the main objective was to test if a classification scheme is able to classify these unknown scenes to their correct category based on the proposed semantic similarity methodology.

After the collection of the geometries from the training dataset and the creation of the synthetic components of the test dataset we proceed with the extraction of the spatial signatures for both datasets using the HoF. Given the fact that the airport ontology is comprised of five components, based on *Equation 8*, as it was described in Section 3.4, we formulate ten possible pair combinations of the constituted components. The following examples present a graphical illustration of the application of HoF in three different conditions.

The first example, as shown in Figure 4.4, describes the case where two objects have a degree of overlap, in the second example, as shown in Figure 4.5, the two objects are disjointed, while in the third example, as shown in Figure 4.6, the one object is included in the other. The information of the extracted spatial signatures has been stored in matrices of dimension 13x360 (13 relations, 360^o), containing actual values that represent topology direction and also distance. Since scene similarity has to be based in comparable quantitative measurements, the aforementioned step becomes essential and will enable a meaningful and accurate comparison using the NCC. As a reminder, the resulting histogram of fuzzy Allen relations in the following figure is a representation of the total area of the part of object A that faces the part of object B in a predefined direction θ, under a specific relation.

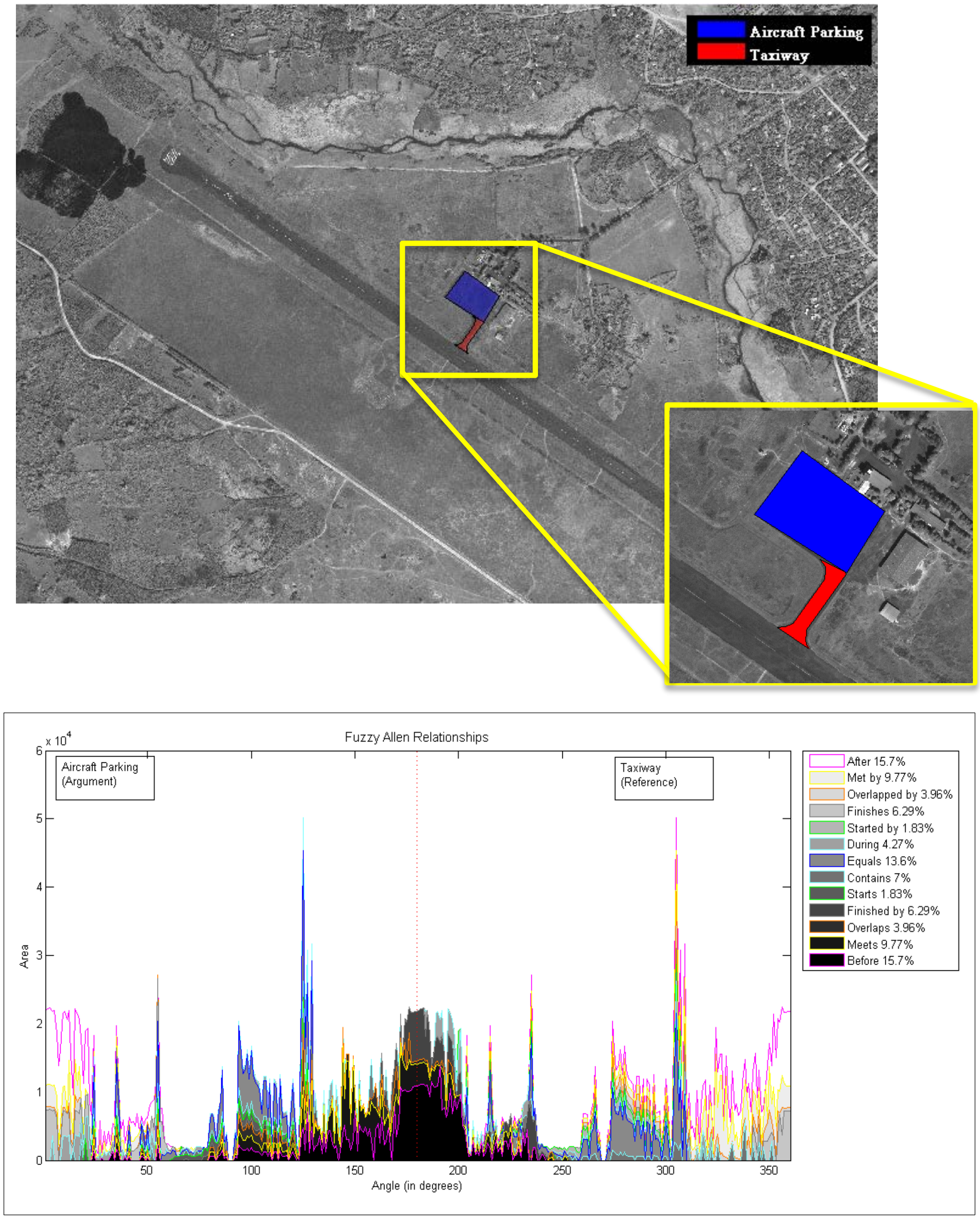

Figure 4.4: Overlap example of resulted fuzzy Allen relations coupled with HoF between the objects Taxiway (argument) and Aircraft Parking (reference). (upper) The two component objects. (lower) HoF and the percentages of each relationship.

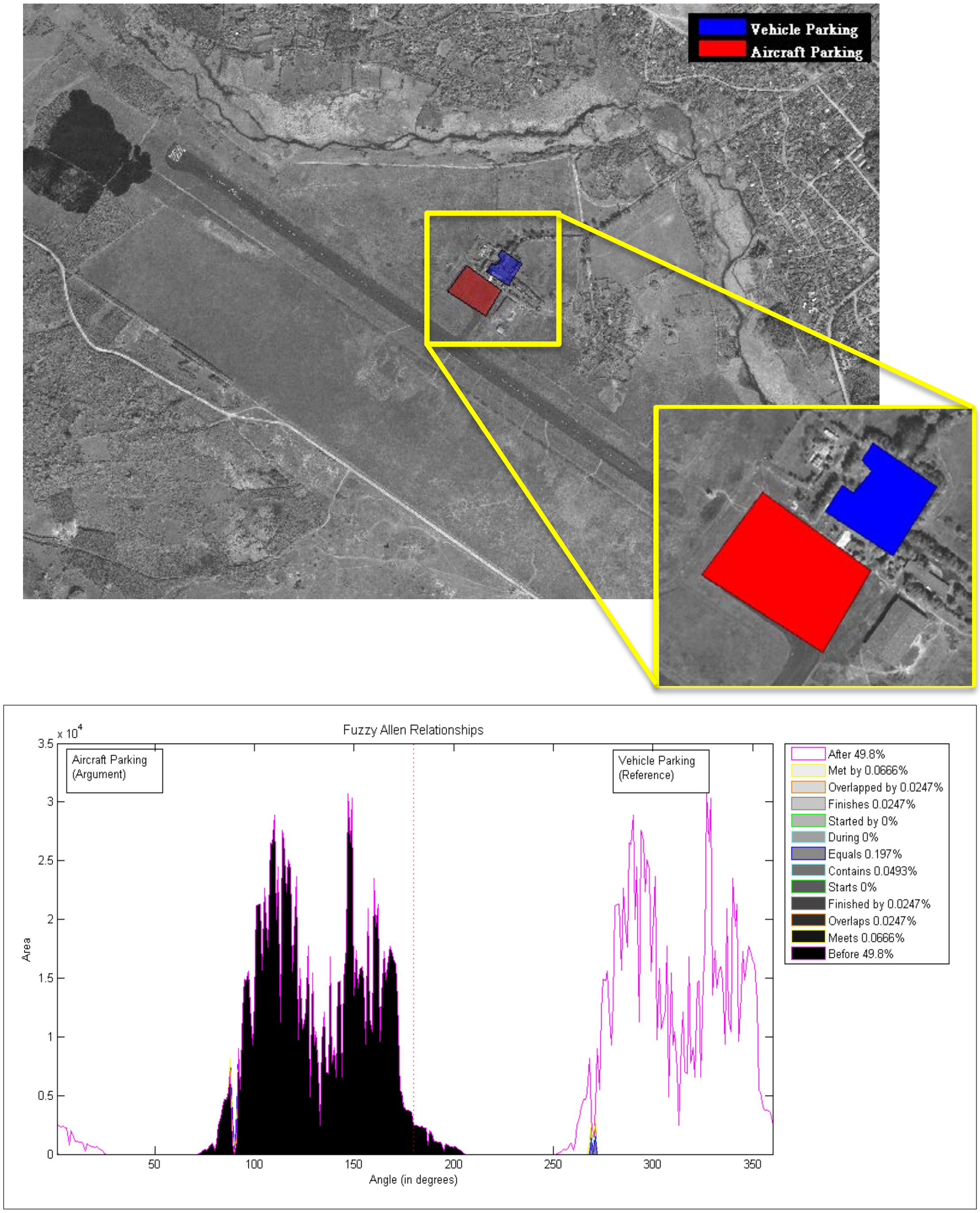

Figure 4.5: Disjoint example of resulted fuzzy Allen relations coupled with HoF between the objects Aircraft Parking (argument) and Vehicle Parking (reference). (upper) The two component objects. (lower) HoF and the percentages of each relationship.

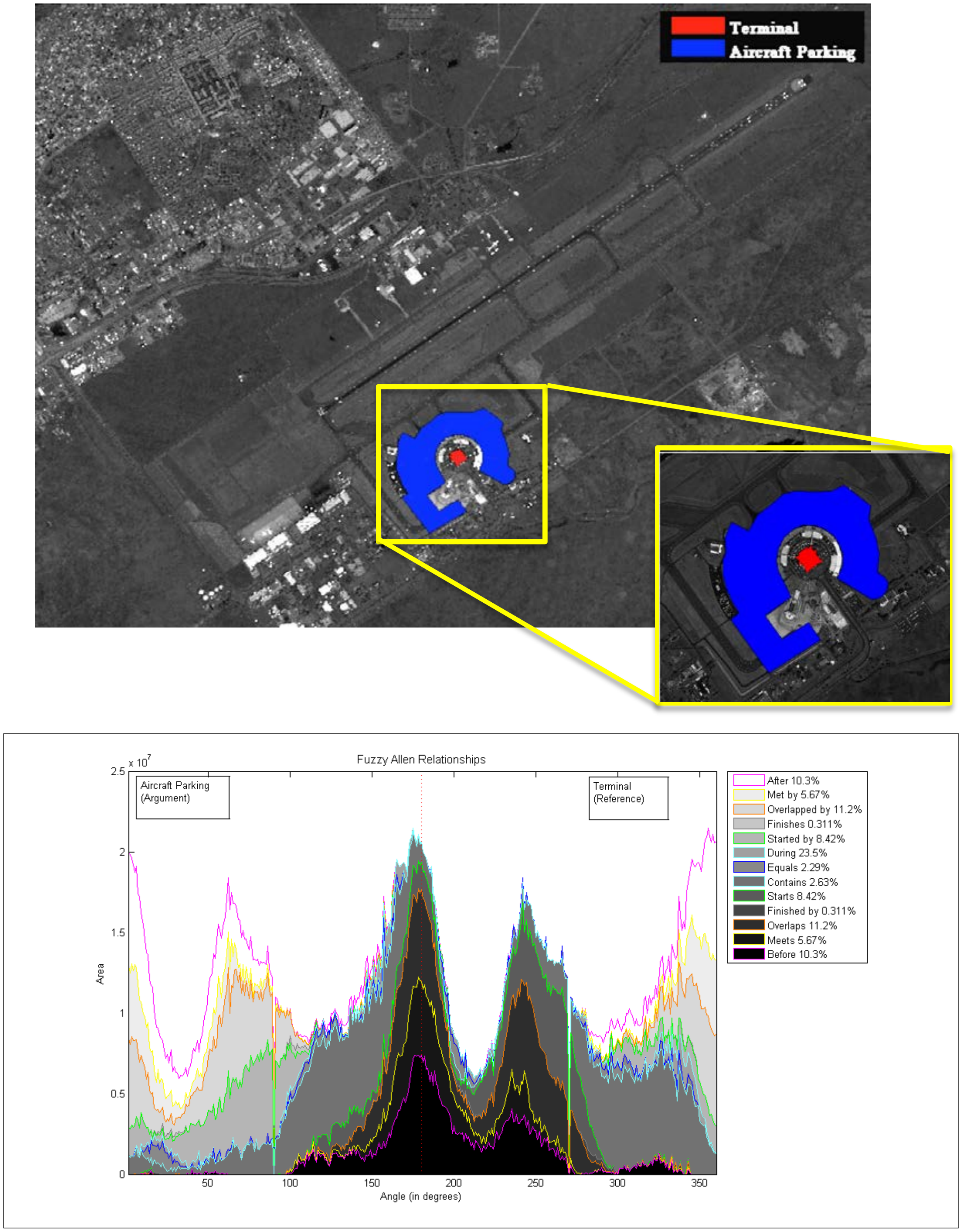

Figure 4.6: Inclusion example of resulted fuzzy Allen relations coupled with HoF between the objects Aircraft Parking (argument) and Terminal (reference). (upper) The two component objects. (lower) HoF and the percentages of each relationship.

As it can bee seen from the three different examles, HoF provide the flexibility on describing relations between more complex shapes such as objects with concave and convex hull shape. Aslo, It has to be noted that among the advantages of this approach, it is also sensitive to distance although it provides combined information about topology and direction. For example, if the distance of the two objects in Figure 4.5 increases, it will reflect on the distance between the two curves at the corresponding HoF.

The next step for the calculation of the semantic scene similarity procedure was the implementation of the spatial calculus based on the NCC. The above illustrated HoFs, as it was mentioned, were translated into matrices that contain the values of each of the 13 relationships between an object pair, in the direction $0^o – 360^o$. At this level the NCC is applied between every object pair of the testing / synthetic airports and the training / real airports. Given the fact that we have 10 unique object combinations for each airport we calculate each pair of the training data with the corresponding of the test data. For example, for the extracted relations between A (Runway) and B (Taxiway) the calculation will be: NCC (AB_{test}, $AB_{training\_1}$)…NCC (DE_{test}, $DE_{training\_1}$). After finding the correlation coefficient (0 – 1) for every corresponding object pair between the tested airport and all the other training airports of the same category then we calculate the average value of all the coefficients and the similarity score is derived.

In order to verify the proposed scene-matching scheme we tested the synthetic airports against the training airports to see how they classify in the correct category. We run the experiments before and after the subset attribute selection to check the effect on the overall results. The experiments have resulted to a correct classification for all the three categories deriving high similarity scores. As it was proven the application of data mining procedure significantly affected the scores providing a more accurate categorization of the scenes and reducing the amount of the processing time, and the overall complexity. In Figures 4.7 - 4.9 the similarity score charts for the three ontology categories before the attribute selection are presented, while in Table 4.2 the corresponding average scores with the standard deviations are presented.

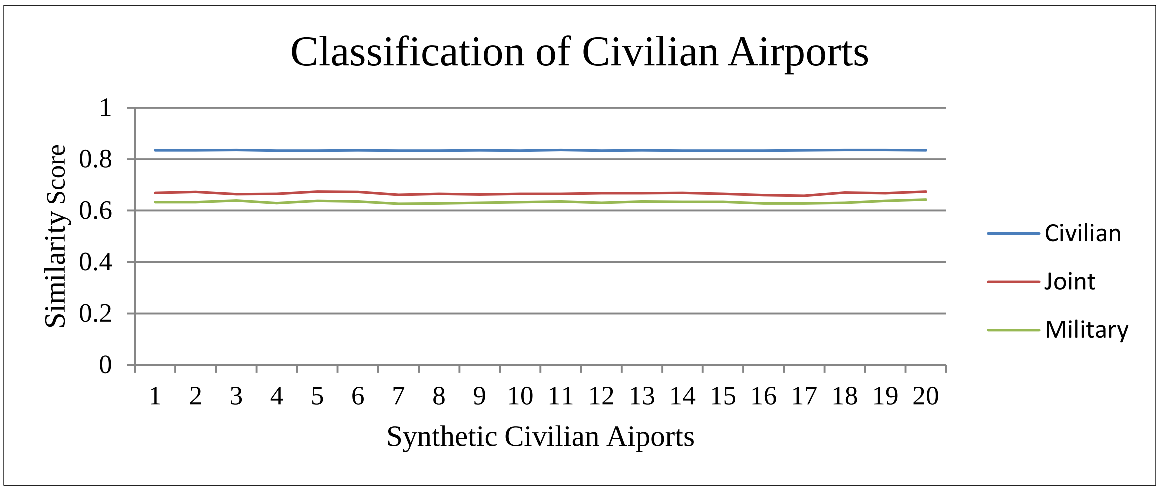

Figure 4.7: Similarity scores for the Civilian class without the attribute selection.

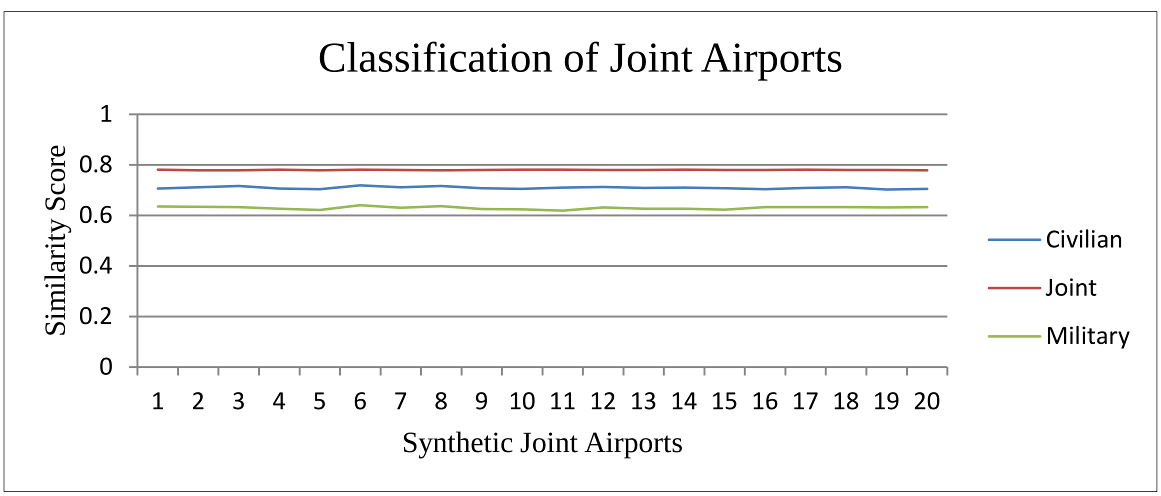

Figure 4.8: Similarity scores for the Joint class without the attribute selection.

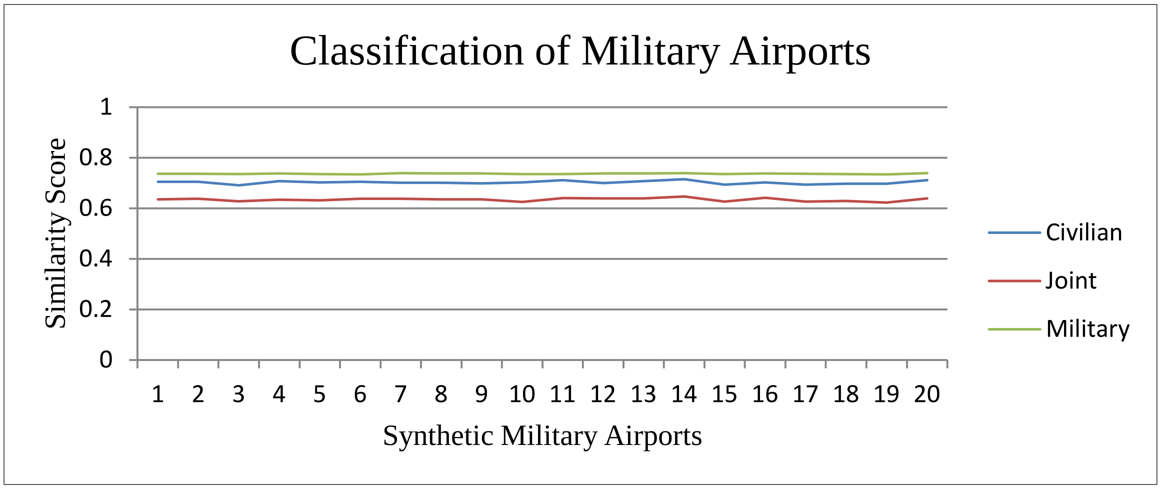

Figure 4.9: Similarity scores for the Military class without the attribute selection.

Table 4.2: Similarity score statistics before the attribute selection.

Civilian Class	**Civilian**	**Joint**	**Military**
Mean	**0.834**	0.667	0.633
St. Dev.	**0.001**	0.004	0.004
Joint Class	**Civilian**	**Joint**	**Military**
Mean	0.709	**0.779**	0.623
St. Dev.	0.004	**0.0009745**	0.006
Military Class	**Civilian**	**Joint**	**Military**
Mean	0.702	0.634	**0.737**
St. Dev.	0.006	0.006	**0.002**

As it can be seen from Table 4.2 as well as from Figures 4.7 - 4.9, the synthetic scenes have higher similarity scores to their corresponding category indicating a correct categorization. The mean values denote that there is a sufficient difference of the correctly classified airports with respect to the category where they actually belong to. Concerning the standard deviation, the low values indicate that data are clustered closely around the mean, which shows higher reliability of the classification. In the following figures (Figures 4.10 - 4.12), the similarity score charts for the three ontology categories after the attribute selection are presented; while in Table 4.3 the corresponding average scores with the standard deviations are presented. An overall chart is presented in Figure 4.13 that illustrates the improvement on the similarity scores after the application of the attribute selection.

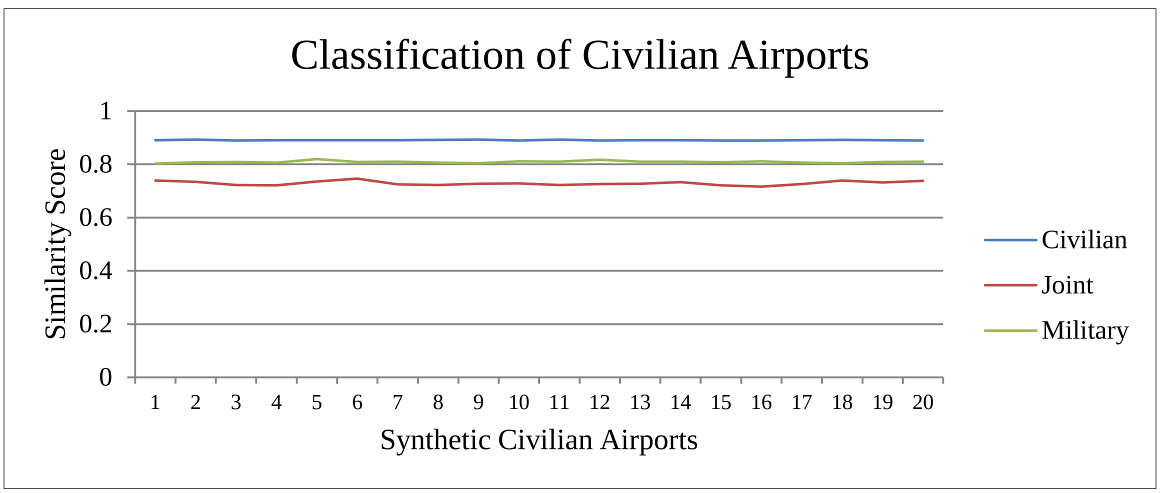

Figure 4.10: Similarity scores for the Civilian class after the attribute selection.

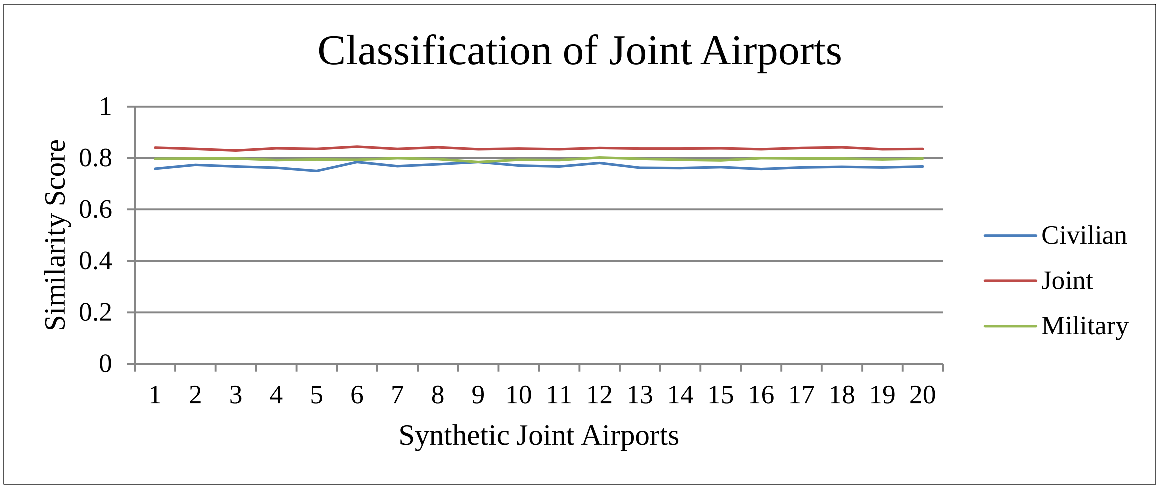

Figure 4.11: Similarity scores for the Joint class after the attribute selection.

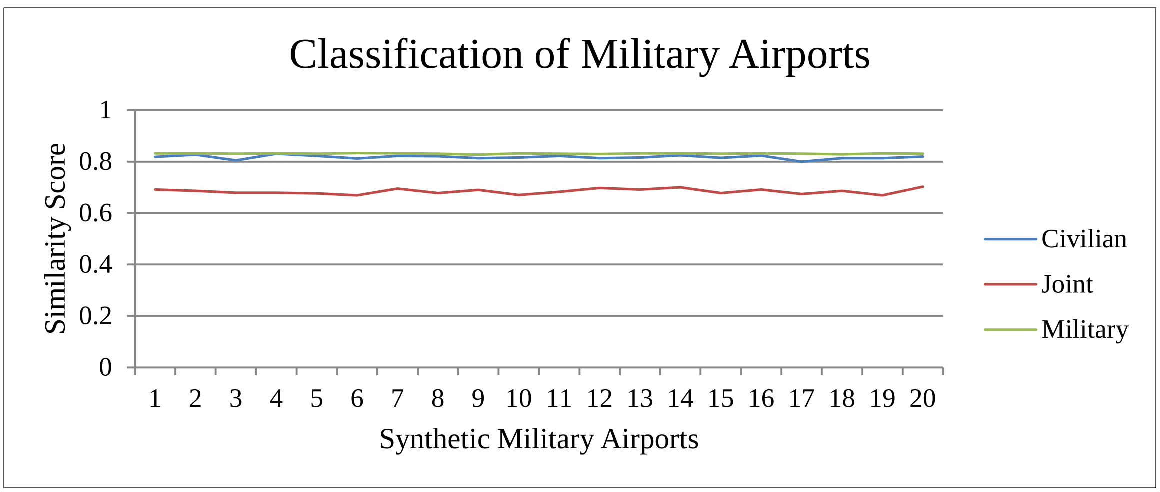

Figure 4.12: Similarity scores for the Military class after the attribute selection.

Table 4.3: Similarity score statistics after the attribute selection.

Civilian Class	Civilian	Joint	Military
Mean	**0.890**	0.729	0.809
St. Dev.	**0.001**	0.007	0.004
Joint Class	**Civilian**	**Joint**	**Military**
Mean	0.767	**0.837**	0.795
St. Dev.	0.008	**0.0034131**	0.004
Military Class	**Civilian**	**Joint**	**Military**
Mean	0.817	0.68438	**0.83**
St. Dev.	0.007	0.01	**0.001**

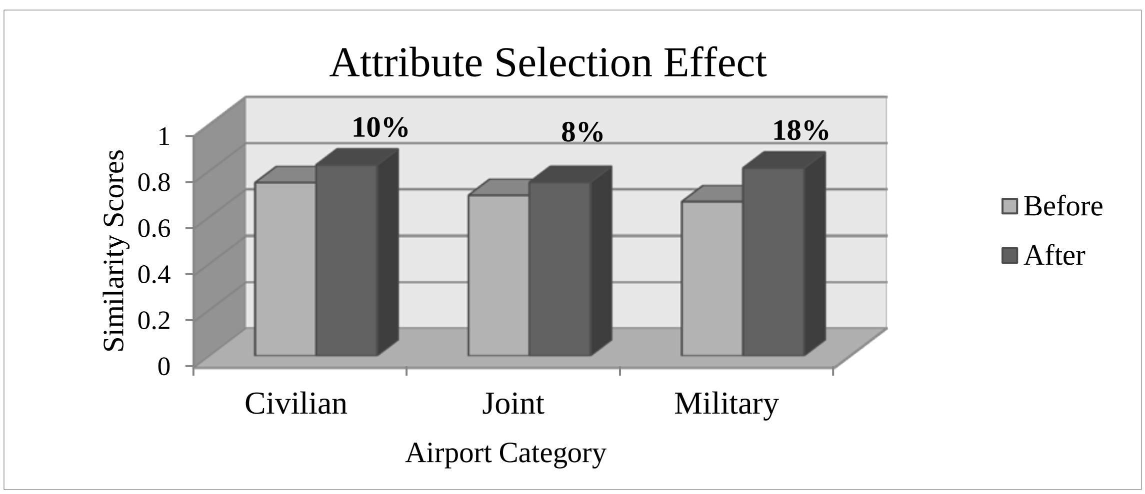

Figure 4.13: Similarity scores improvement for all the ontology categories after the application of the attribute selection.

As shown in Figure 4.12, there is a significant improvement after the selection of the most relevant spatial relations. In overall, the scene-matching for the categories of “Civilian” and “Military” ontologies have higher means of similarity scores as it was expected. The explanation is that the category “Joint” consists of less distinctive class object in comparison with the other two categories since ontologically this category falls in between the other two. Despite this outcome, the classification and consequently the scene-matching in this category remains completely correct and well defined.

After the successful verification of the proposed scene-matching scheme, a final experiment involving the validation of the overall invariance adequacy that can be achieved. For this test, an airport scene from the training data, category “Joint” was selected and distorted by means of scale (30% rescale) and rotation (15%). In continuation, the two scenes, original and distorted have been compared based on the proposed scheme and using only five selected relations. The similarity score was found to be 0.941 that is very high even after the applied distortion proving the adequacy of HoF in invariance in affine properties, which is very critical for the scene similarity purposes. In Figure 4.14 the two images used for the invariance validation are presented.

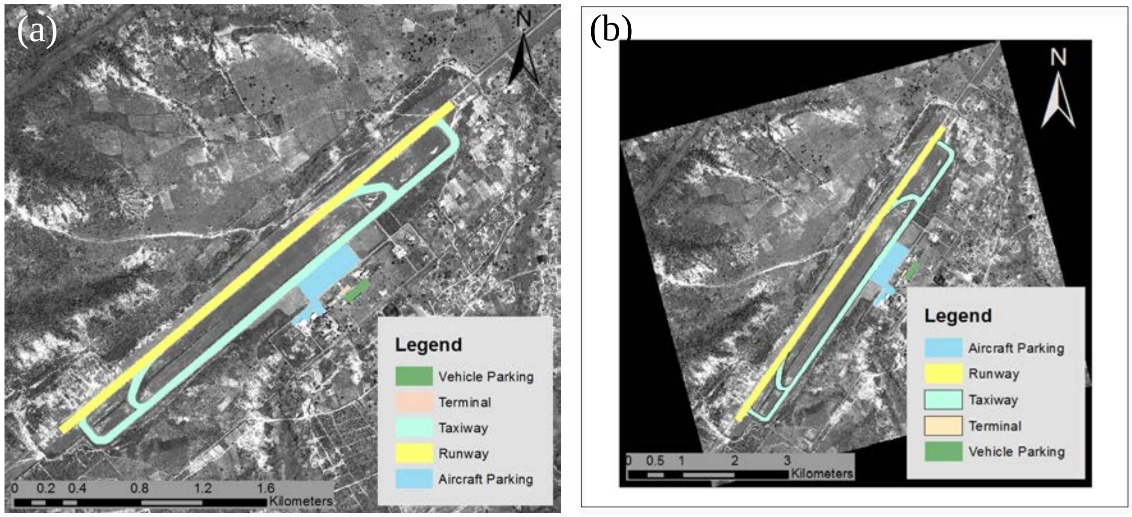

Figure 4.14: Invariance check of HoF (a) Original image, (b) distorted image.

CHAPTER 5: COMPOSITE SCENES IN SOCIAL MEDIA EVENTS

This Chapter presents an application of the proposed methodology described in Chapter 3 to a second test case, which is, a study area comprised of social media feeds for a natural disaster event. In this test case we consider as *transient scenes* the spatial scenes that consist of spatiotemporal clusters describing the responses of the crowd to a certain event. More specifically, in Section 5.2 we are introducing a novel social multimedia triangulation process that uses jointly Twitter and Flickr content in a two-step integrated process in order to delineate the impact area as the overlap of multiple view footprints. In this approach, we practically crowdsource approximate orientations from Twitter content and use this information to orient accordingly Flickr imagery and identify the impact area through viewshed analysis and viewpoint integration, modeling this way the spatial scene of a natural disaster event in order to explore its discernible patterns and their similarities. The results of the application of semantic similarity assessment in this test case are presented in Section 5.3.

5.1 Introduction

Fostered by Web 2.0, ubiquitous computing, and corresponding technological advancements, social media have become massively popular during the last decade. The term social media refers to a wide spectrum of digital interaction and information exchange platforms, ranging from blogs and micro-blogs (e.g. Twitter, Tumblr, and Weibo), to social networking services (e.g. Facebook), and multimedia content sharing services (e.g. Flickr and YouTube). Regardless of the particularities of each platform, these social media services share the common goal of enabling the general public to contribute, disseminate, and exchange information (Kaplan and Haenlein, 2010). Traditional web-accessible information has always been rich in geographic content (Silva *et al.*, 2006), and this of course remains true for social media content. But in addition to geographical references within the data, social media is also becoming increasingly geotagged as a result of the proliferation of location-aware devices (Hurst *et al.,* 2007; Valli and Hannay, 2010; MacEachren *et al.*, 2011; Stefanidis *et al.*, 2013b). Accordingly, social media content is emerging as a rich source of geospatial information, presenting our community with many opportunities and challenges (Sui and Goodchild, 2011). The opportunities are primarily associated with the potential of these crowdsourced data to complement authoritative datasets by contributing timely information (e.g. Gao *et al.,* 2011). The challenges are reflections of the very nature of these datasets: diverse data structures and formats, and variations in quality and accuracy (Agichtein *et al.,* 2008).

Driven by the allure of opportunity, the geographical community has been experimenting over the past few years with harvesting geospatial information from social media content. For example, studies addressed the use of Twitter reports to gain knowledge regarding the breaking and progression of natural disasters such as wildfires (De Longueville *et al.,* 2009), earthquakes (Crooks *et al.*, 2013) and flooding (Fuchs *et al.*, 2013). The spatiotemporal analysis of Twitter content has also been used to track disease outbreaks (Signorini *et al.,* 2011; Sugumaran and Voss, 2012), or to identify the formation of international communities and the communication of information during political crises (Stefanidis *et al.,* 2013a). While these studies are advancing our ability to understand the geospatial content of social media and the manner in which they are used to communicate various forms of information, they were primarily focused on just a portion of social media content: text. However, social media content information is not just textual. Flickr and Instagram offer massive records of imagery, and YouTube videos are rich in visual content, providing an additional dimension through which information is communicated. Some early attempts to exploit the content of these additional services have primarily focused on the analysis of point patterns. For instance, Li and Goodchild (2012) studied point patterns of georeferenced Flickr imagery in conjunction with toponyms in their metadata to identify places through user references to them. Other efforts attempt to recognize activity and behavioral patterns by analyzing these spatiotemporal points of geotagged entries, such as identifying attractive destinations (Kisilevich *et al.,* 2010) or constructing travel itineraries (De Choudhury *et al.,* 2010).

Despite these efforts, the multimedia content of social media remains underexplored. In this paper we contribute towards bridging this research gap by examining the benefits of the complementary use of heterogeneous sources of social multimedia feeds to assess the impact of a natural disaster. More specifically, we are introducing a novel social multimedia triangulation process that uses collaboratively Twitter and Flickr content in a two-step integrated process: Twitter content is used to identify toponym references associated with a disaster; this information is then used to provide approximate orientation for the associated Flickr imagery, allowing us to delineate the impact area as the overlap of multiple view footprints and therefore to model the scene in order to explore its discernible patterns. In this approach, we practically crowdsource approximate orientations from Twitter content and use this information to orient Flickr imagery and identify the impact area through viewshed analysis and viewpoint integration. This approach allows us to triangulate numerous images by having them pointed towards the crowdsourced toponym location while avoiding computationally intensive image analysis tasks associated with image orientation (e.g. the identification of conjugate features). In this study case we present an approach and demonstrate its performance using a wildfire event as a representative application.

5.2 An Updated Scene Model

One of the most challenging tasks in this case study is the scene modeling adequate to incorporate the semantics of a transient formatted scene as well as capable of handle the ambiguity and vagueness that describes a spatial scene of this type. That becomes critical in the case where we do not have a scene in a built environment where its constituted components are well-defined buildings such as in the first test case but instead we have clusters of information in space, which is more conceptual and fuzzy. Based on the main argument of the ontologically-driven semantic similarity framework that was described in Chapter 3, the scene modeling and therefore scene comparison task becomes a solvable problem since this approach enables us to handle this type of scenes and geospatial information as well.

As we observe there are discernible patterns when it comes to event reports in social media. These patterns comprise (at least) three main components: the event location itself, the locations (or clusters of locations) from which social media reports are provided, and the urban space in the event vicinity. There may be multiple granualarities associated with this analysis, whereby the event may be for example a major fire few miles away from a city, all the way down to a highly localized event in a town square. In this dissertation, in order to be consistent with the study that we presented in Chapter 4, we are focusing on events at a scale that can be monitored through traditiobnal remote sensing techniques, and thus focus on an event scale comparable to the former (fire some miles away from a city) rather than the latter (small, highly localized event).

Consequently, in the given study case, a transient scene can be considered as an ontology comprised of the actual area of the natural disaster (wildfire in our case), the disseminated and/or user generated information about this incident and the reference location/area that is impacted from this event such as the nearest city. All three components of the event's feature class contain both geospatial information as well as contextual information by the social media feeds. While the two of the three components have an actual spatial extend the challenging part at this point is the delineation of the impact area provided by the social media. In the following figure (Figure 5.1) are illustrated the component objects of a wildfire event feature class.

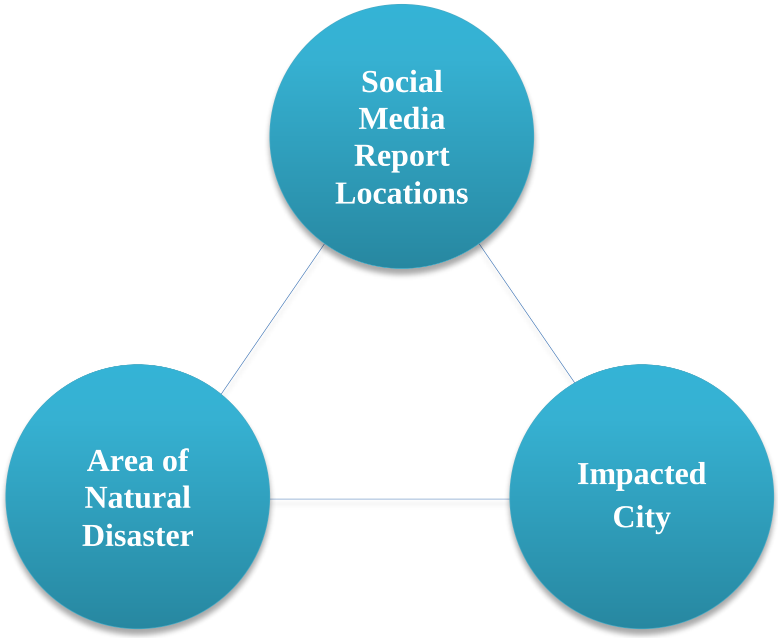

Figure 5.1: Component objects of a wildfire event feature class.

5.2.1 A Cross-Source Triangulation Framework

As discussed above, our main objective is to integrate social media content referring to an event (e.g. a natural or anthropogenic disaster) across sources in order to advance our capability to geolocate this event and delineate its footprint. In order to meet this objective we introduce a novel multimedia triangulation framework[2]. Through this framework, contribution patterns are extended from simple point clouds (indicating the location of the contributors) to become the equivalent of views of a particular event (which involve an understanding of the relationship between the contributor and the event). These views can then be synthesized to delineate the event footprint via viewshed

[2] Parts of this Section were published in Panteras *et al.* (2014)

analysis. We accomplish this goal through the two-step process that is summarized in Figure 5.2. The first component of our approach entails Twitter content analysis for the identification of toponym references associated with the event of interest (presented in Section 5.2.2). Using this information we then harvest Flickr imagery using geolocation and tag constraints: we query the Flickr Application Programing Interface (API) to retrieve images from the broader vicinity of the toponym, and with tags that are related to it as well. These images are then oriented using the toponym information as a reference point, and their viewable area footprints are integrated via viewshed analysis in order to derive an estimate of the event footprint (as a probability map), (in Section 5.2.2.2). The underlying assumption in our approach is that tweets contain references to the location of the event, whereas Flickr contributions provide views of it. This methodology represents a cross-platform social multimedia analysis approach for event triangulation.

While Twitter is utilized in this framework to derive the approximate location of a given event (which can then be further refined using Flickr), it should be noted that other sources may also be exploited for the extraction of such information. For example, a toponym reference can be extracted from other communication avenues, such as news media feeds or blogs, which could substitute the Twitter reference point extraction process in Figure 5.2. Another source of such information may very well be Flickr itself, as image annotations may contain toponym references. However, such annotations in Flickr tend to vary in terms of their frequency (Ames and Naaman, 2007; Nitta et al., 2014), thus potentially limiting the suitability of Flickr annotations alone for this purpose. This is further attenuated if we consider the data volume differences between Twitter and

Flickr. For example in this particular study, the number of Flickr contributions is roughly 0.5% of the number of tweets reporting the same event. This is consistent with the reports of overall data traffic associated with these two social media services (Croitoru et al., 2014).

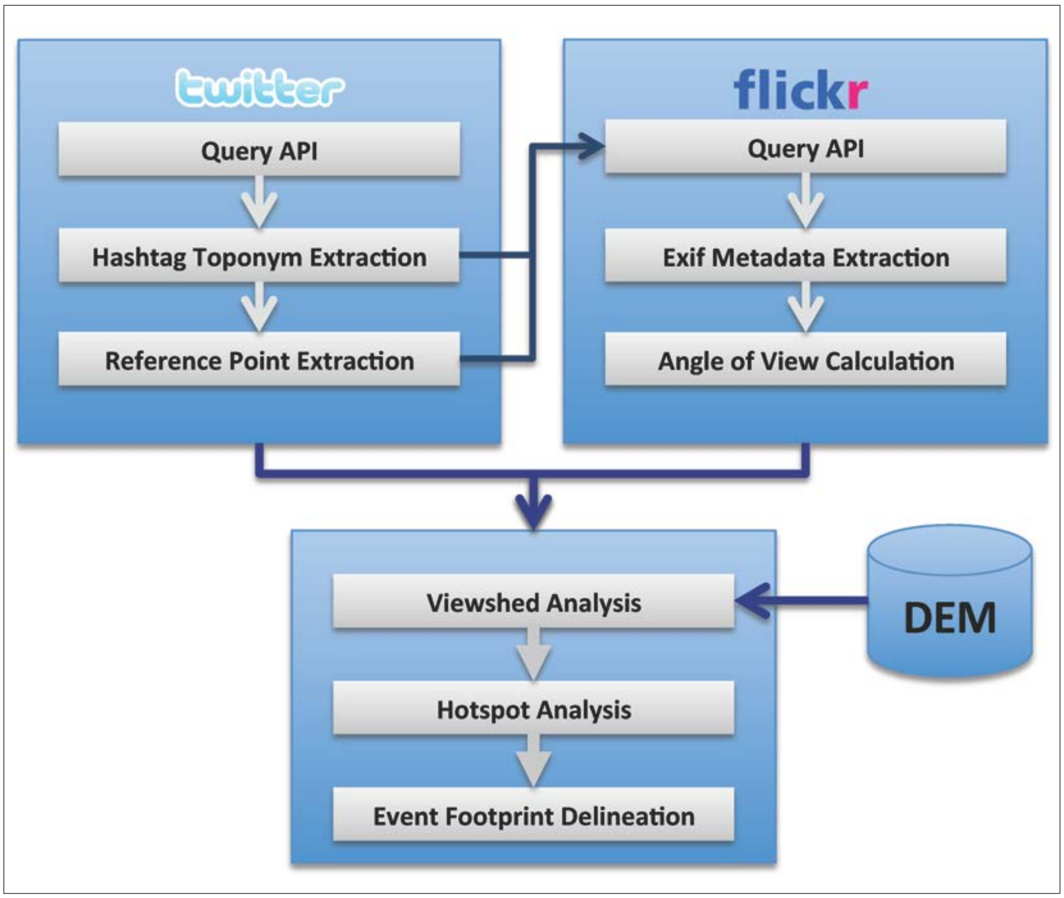

Figure 5.2: The cross-source triangulation framework.

5.2.2.1 Event Localization using Toponym References in Twitter

In order to best communicate how the various components of our framework are operating and integrated, we use the 2012 wildfire of Waldo Canyon in Colorado Springs (Colorado, US) as a case study. The wildfire started in June 23, 2012 and was not fully contained until July 12, 2012 (the study period), which is used as the study period in this paper. During that time, the wildfire consumed a total area of 74 km^2, and was considered the most destructive wildfire in Colorado's history at the time based on the extent of damage to property (McGhee, 2013). Figure 5.3 provides an overview of study area, showing Waldo Canyon to the northwest of Colorado Springs, with the actual wildfire area overlaid along with the location of geolocated Flickr images during the event.

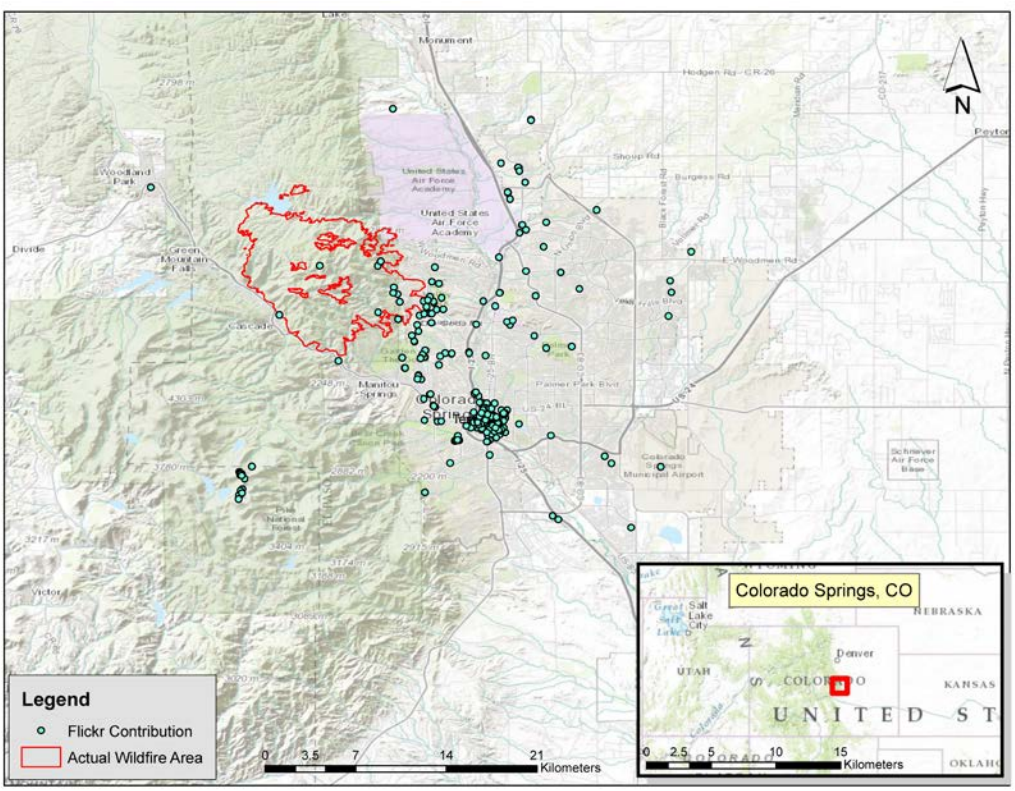

Figure 5.3: Overview of the study area.

We collected relevant Twitter data from the Twitter API using the keyword ‘Fire’ over the study period, resulting in a corpus of 97,866 tweets among which 41.4% are retweets. It is worth noting that as we analyze the content of tweets rather than their spatial distribution, the presence of relatively high retweet levels is likely to contribute to the emergence of toponyms in our data corpus, thus further facilitating the detection of the relevant toponyms. We therefore view retweeting as a crowdosourced curation process, whereby the general public weighs upon twitter content and assigns gravity to it in a variety of ways, with retweeting being the most prominent (e.g. Boyd *et al.,* 2010).

The content of the tweets corpus was analyzed in order to generate the word-cloud shown in Figure 5.4. This entailed parsing the text to remove all non-hashtag punctuation (e.g. emoticons), removing articles, and converting all text to lowercase. The word-cloud visualizes the frequency of individual words in our Twitter data corpus, with larger words been encountered more frequently. It is easy to observe that, after the word fire (which was the keyword used to query the Twitter API for this study) the predominant terms that emerge are geographical in nature, with ‘Waldo’ being the dominant among them – either by itself or as a part of a compound hashtag. This heavy use of geographical references in social media narrative when reporting natural disasters has also been noted in other natural disaster studies. Vieweg *et al.* (2010) stated that in their studies toponym references were present in as many as 40% of tweets reporting wildfires and 18% of tweets reporting flooding. This is also consistent with studies addressing the broad presence of toponyms in reporting various types of breaking news (Lieberman and Samet, 2011; Stefanidis *et al.*, 2013a).

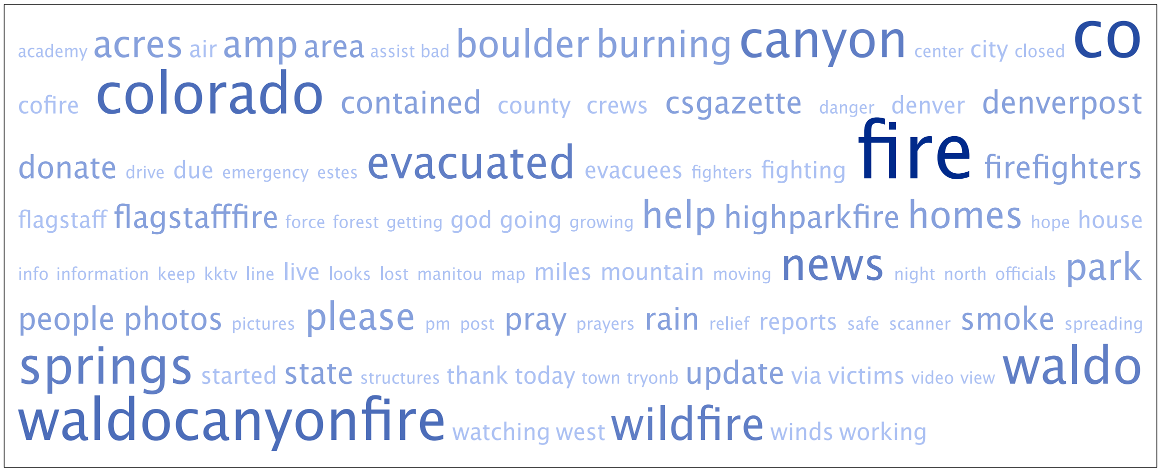

Figure 5.4: Word-cloud of Tweeter most frequent terms and hashtags during the wildfire.

The Twitter data corpus was then converted to lowercase and filtered to extract all hashtags. Figure 4 shows the frequency over time of the 10 most popular hashtags for the duration of the wildfire event. As can be seen from it, '#waldocanyonfire' has emerged as the top hashtag associated with this event, a term which encompasses both the nature of the event and the location of it. The emergence of hashtags like this through a bottom-up process, from the crowd and adopted by the crowd, serves as further indication for the value that the public places on the locational information when referring to major events such as this. In fact, all 10 most popular hashtags were of the form {'#',<location>,<event>}.

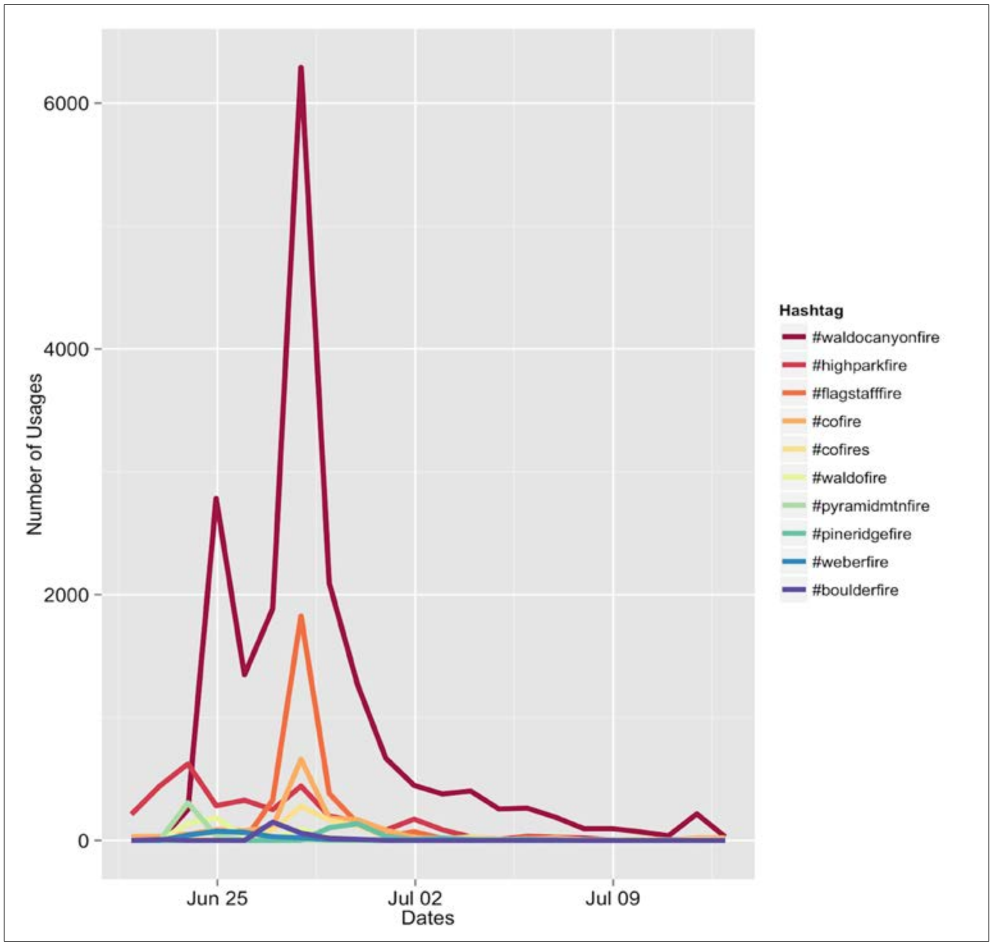

Figure 5.5: Usage of most frequently adopted hashtags over the wildfire period.

Similar to Figure 5.5, in Figure 5.6 we show the frequency of the 10 most popular toponym references in the Twitter narrative associated with the event. The results confirm the popularity of Waldo Canyon, while also suggesting the emergence of a hierarchical structure in the toponym references, with the State (Colorado) leading, and the particular area within it (Waldo) following. The remaining toponym references relate to the areas that were secondarily affected by the wildfire event, e.g. Flagstaff Mountain, and the smaller towns of Manitou and Estes. In our case we selected the toponyms manually for quality control purposes, however this process can be automated using a gazetteer. Using Waldo Canyon as the prominent location in the Twitter corpus, we retrieved the point location of this toponym from a gazetteer (Google Geocoder), and used it as the reference point of the event in subsequent analysis. Once the approximate geolocation of the event is determined through the analysis of Twitter content (toponyms and hashtags) we proceed with the analysis of Flickr contributions to delineate the impact area of this event, as described in Section 5.2.2.2 below.

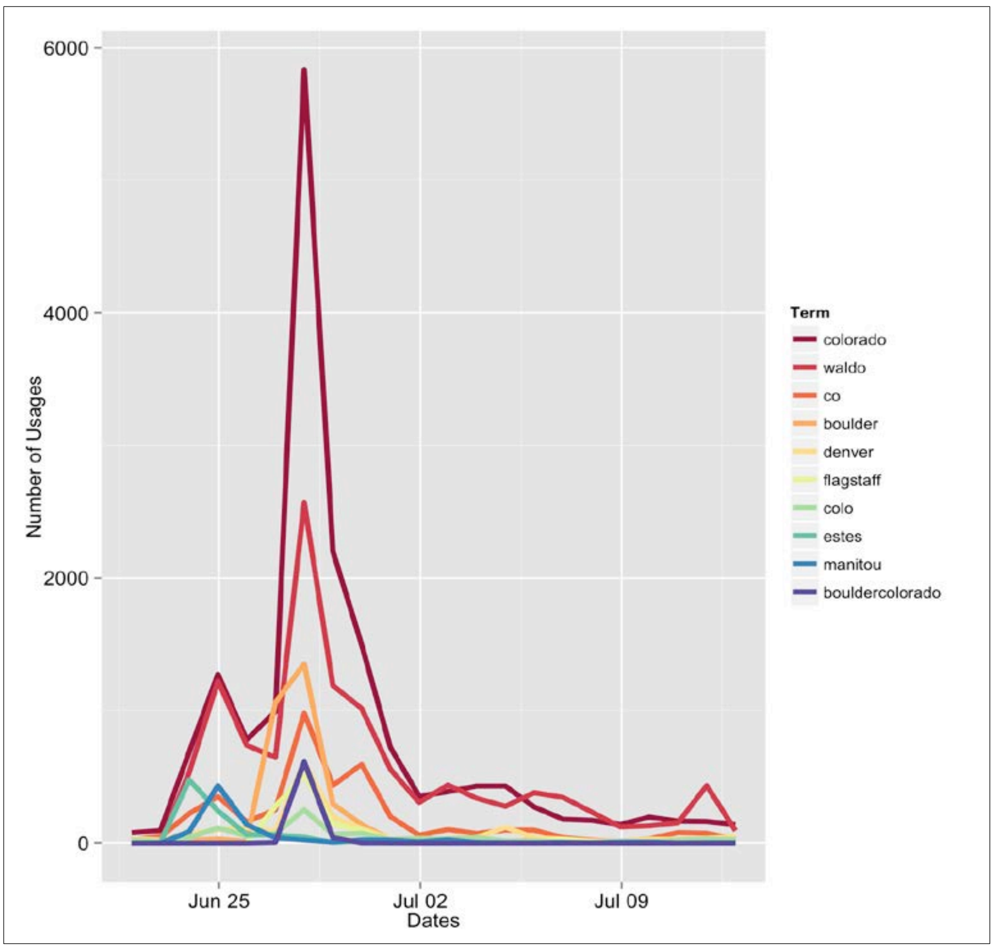

Figure 5.6: Usage of most frequently adopted toponym terms over the wildfire period.

5.2.2.2 Impact Area Delineation through Viewshed Analysis of Flickr

While Twitter provides textural information of the event, Flickr provides us with visual evidence of the event in the form of images. Such information is often accompanied with geolocation information either as exact geographical coordinates (via metadata), manual placement of the image on a map (via the Flickr map interface), or as an approximate location (via geographically relevant keywords, i.e. toponyms). In our study we utilize the imagery metadata, which is provided in the Exchangeable Image File (Exif). Exif data provides a range of metadata about the contributed image, including detailed information about the date and time, focal length (f_c), image dimensions (L) and shutter speed. In addition, information about the model and the make of the sensor can be found. Based on such information, all the camera specifications can be retrieved from existing online databases. Finally, in some cases information concerning the direction of view of the image can be found under various Exif fields, for example the "GPS Direction" which is provided when the camera device is equipped with either GPS or electronic compass. However, such information is often lacking.

Flickr data can be retrieved through a dedicated API[3], similarly to Twitter, which supports the user-defined queries. For our study we retrieved data based on a number of query parameters: (a) photos must be geotagged (i.e. *has_geo=1)*; (b) photos must have the tags wildfire and Colorado (i.e. *tags="wildfire,colorado", tag_mode="all");* (c) photos must have the title or description that contains Waldo Canyon Fire (i.e.

[3] http://www.flickr.com/services/api/flickr.photos.search.html

text="Waldo Canyon Fire"); (d) photos must be within a bounding box (bbox) defined by the study area (i.e. *bbox="-105.316,38.523,-104.291,39.224"*); and (e) the time stamp of the photo must be in the time period of the study (i.e. *min_taken_date="2012-06-24", max_taken_date="2012-07-04"*). Using these parameters a total of 427 images were retrieved of which only 191 (less than 50%) had Exif information. However, while for some of these images the angle of view (AOV) can be derived from Exif information, none of these images included the observer's orientation (i.e. azimuth). This fact, which appears to be frequent in Flickr data (Wueller and Fageth, 2008), serves as one of the primary motivations for developing our viewshed analysis methodology. As a result, we use the coordinates of the toponyms and the Exif information to derive both the direction of view (as estimated by the azimuth) and the AOV (as estimated from the focal length and the image size), which we turn to next.

As expected, the contributions in this case are consistent with observed social media and blogosphere patterns (e.g., Stefanidis *et al.* (2013) and Shi *et al*. (2007) respectively): approaching a power law distribution, with few users contributing large portions of the data, and a majority of users making minimal contributions. In our case study the 427 Flickr images that were retrieved were contributed by 38 distinct users, with the median contribution per user being 1 photo (compared to the average of 11). This deviation between the median and the average values is indicative of the degree of skewness of the contributions among users.

5.2.2.3 Azimuth and Angle of View Calculation

The purpose of estimating the azimuth and the AOV is to orient and constrain the extent of the view from each image location. For this purpose, we first establish the AOV using the sensor parameters (i.e. focal length and image dimensions as provided by the image Exif file), and then orient the AOV by calculating the azimuth between the observer location and the event reference point. Generally, three AOVs that can be calculated for a given image: the horizontal, the vertical, and the diagonal. As our objective is to establish the extent of the footprint of the event (i.e. wildfire), we utilize the horizontal AOV, which is calculated as:

Equation 9: Calculation of the horizontal AOV, φ_{AOV}.

$$\varphi_{AOV} = 2tan^{-1}\left(\frac{L}{2f_c}\right) \tag{9}$$

where L is the image width and f_c is the sensor focal length. Using equation (9), the AOV has been calculated for the 191 images for which an Exif file was available. For the remaining 236 images that did not include Exif metadata, the average of the 191 AOVs that were calculated using the Exif data was used as an approximation. Considering that Flickr imagery is increasingly contributed by mobile devices with relatively similar camera characteristics[4], the use of an average value for imagery lacking AOV information is a reasonable approximation (Singla and Weber, 2011).

[4] https://www.flickr.com/cameras

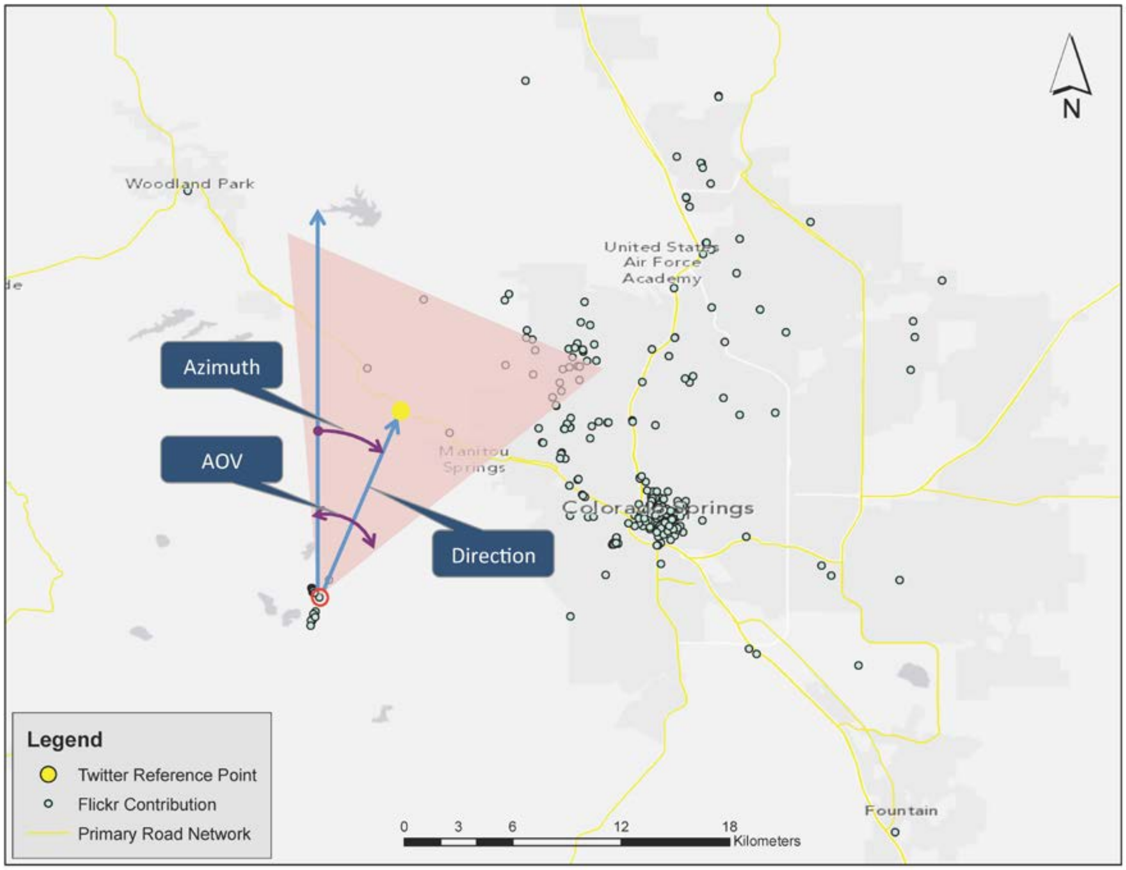

Figure 5.7: The AOV and azimuth of a given Flickr image.

In order to orient the AOVs, we calculated the azimuth between each image location and the event reference point (as described in Section 3.1). More specifically, the calculation of the azimuth for every image was based on the geodetic azimuth using the following formula (Yang *et al.*, 1999):

Equation 10: Calculation of the geodesic azimuth, θ.

$$\theta = tan^{-1}\left(\frac{\sin(\lambda_2 - \lambda_1)\cos(\varphi_2)}{\cos(\varphi_1)\sin(\varphi_2) - \sin(\varphi_1)cos(\varphi_2)cos\,(\lambda_2 - \lambda_1)}\right) \tag{10}$$

where, φ_1, λ_1 and φ_2, λ_2 are the geographical coordinates of the Flickr image location (or the observer) and the event reference point respectively. As a result of this calculation, each Flickr image is now associated with a geographic location and an oriented AOV from which a viewshed analysis can be carried out in order to delineate the footprint of the event.

5.2.2.4 Viewshed Analysis

The information extracted in the previous section (i.e. the event reference point, and the azimuth and AOV of each image) can be utilized for estimating the *footprint* of the event we analyze. The underlying principle of this estimation process is that observers that contribute images related to the event are doing so from locations at which the event is visible. It should be noted that here we do not assume that the viewable area of all images is identical, but that these viewable areas share one or more *common* areas that are of interest. Based on this, we apply a crowdsourcing approach for estimating the footprint of the event: while each observation may cover a different viewable area and a corresponding footprint on the ground, by *superimposing* all footprints we can derive an estimation of the event footprint. This process can also be seen as a spatial voting process, were each observer – through the contributed Flickr image – casts a vote on the location of the event in the form of a viewable area. The accumulation of these votes, as measured per unit area in the form of a heat map, can then lead to “hotspots” in which the event is most likely to be found.

In order to estimate the footprint of the event through the superimposition of the footprints of individual views, we must first calculate the footprint of each view separately. Given a viewer location, an AOV and a view direction, the problem of estimating the footprint can be transformed into a viewshed analysis problem. In this problem setting, the viewer parameters are used together with a Digital Elevation Model (DEM) of the area for finding the visible areas of a surface from a given observer location. Viewshed analysis is a well-established technique, which spans across various application areas, from navigation and site selection to landscape planning and telecommunication systems (e.g., Nagy, 1994; Fisher, 1995; De Floriani and Magillo, 2003, Sander and Manson, 2007). In our framework, viewshed analysis is utilized to calculate the viewable areas (or cells in the case of a raster grid) between observer and points in the study area, given the reference point of interest (i.e. the event reference point) based on the elevation difference between these points. By systematically applying this calculation to all cells in the study area, we generate a binary map showing the viewable area for each observer. The superimposition of all binary maps for all observers then results in a heat map, where each cell in the map accumulates the number of times the cell was flagged as viewable. It should be noted that while here we assign the same weight to each binary viewshed map during the superimposition process, other weighting schemes could be applied in order to enhance the heat map fidelity for a specific purpose. For example, given a time interval, viewshed maps may be weighted according to their timestamp in order to generate a heat map that highlights the extent of the wildfire during that time interval. However, as in this case study we aim to explore the full extent of the fire, this option was not pursued.

The implementation of the viewshed analysis was carried out in the ArcGIS environment through a workflow consisting of a set of python scripts. This workflow, which systematically applies the viewshed calculation for each image in our data set, provides the ability to control the calculation parameters used. In particular, for each image we set the angular limits of the viewshed calculation as the left and right azimuths of the AOV of the image (which can be derived from the AOV and the azimuth of each image), and set a minimum and a maximum range parameter (measured from the viewer's location) to limit the distances from the viewer for which the viewshed calculation is carried out. The values of these range parameters are set as a function of the average distance between the event reference point and the location of each Flickr image. It is worth noting that in our experiments we utilized the National Elevation Data (NED) data, a 10-meters resolution DEM that is available through the United States Geological Survey (USGS). The final step of our viewshed analysis includes the superimposition of all viewshed raster grids, resulting in a heat map. Cells having high values in this heat map indicate locations that have been visible more in Flickr imagery in relation to the event, while cells having low or zero values indicate locations that have not been visible in such imagery. Based on these values, we can then we analyze hotspots the heat map in order to identify highly visible locations, i.e. locations that were of interest to many viewers on the ground.

5.2.2.5 Hotspot Detection

In the final step of our framework we utilize the heat map that was generated in order to identify hotspots and delineate their extent as an approximation for the footprint of the wildfire event. Here, we refer to a hotspot as a spatial cluster of cells for which high heat map values exist, i.e. clusters that are highly visible to observers in the viewshed analysis. Several well-studied spatial analysis methods exist for the detection of hotspots, among which are Kernel Density Estimation (KDE), Moran's I, and Getis-Ord (Gi*) (Kuo *et al*., 2012). KDE, which is based on a spatial filtering process, produces a smooth density surface by estimating the surface density (Silverman, 1986; Xie, 2008). However, a key difficulty in implementing KDE is the filter bandwidth as well as the ability to test the statistical significance of the results.

Another possible measure is Moran's I, which estimates spatial autocorrelation among similar (low or high) values. While Moran's I could be used for detecting hotspots, its inability to automatically distinguish between high or low hotspots (Griffith, 1987) limits its usability for our purpose. In view of these limitations, we utilize the Getis-Ord Gi* statistic (Ord and Getis, 1992), which enables one to identify statistically significant spatial clusters of both high cell values ("hotspots") and low cell values ("cold spots") in the heat map. A key advantage of the Gi* statistic is that it allows testing the results for statistical significance using calculated z-scores. In order to identify hotspots in the viewshed heat map we applied the Gi* statistic to the heat map, calculated the corresponding z-scores, and used them to generate four classes. Due to the fact that we need to find the most significant hot spot in order to reduce the identification of hot spots to a single one, the null hypothesis was performed appropriately by maximizing the z-score values (Goodchild, 1986). Hence the hot spots analysis was based on the following p-value thresholds: 90% significant (z-score $\geq$1.645), 95% significant (z-score $\geq$1.960), 99% significant (z-score $\geq$2.576), and 99.9% significant (z-score $\geq$3.291). All non-significant cells were grouped in a fifth class. It should be noted that by overlaying two or more significant level heat maps it is possible to generate a heat map of significance level ranges. For example, overlaying the 95% significance heat map on top of the 90% significance level would result in three types of pixels, namely pixels below 90%, between 90% and 95%, and above 95%.

5.3 Experiments and Results

In order to showcase the utility of our approach in a real-world crisis setting as well as to formulate the necessary ontologies for the applicability of the semantic scene similarity we applied it to the 2012 Waldo Canyon wildfire. For this purpose we collected both Twitter and Flickr data, as discussed in Section 5.1, and applied the proposed analysis framework in every day of the event separately in order to delineate the impact area of the fire using our cross-sourced triangulation approach and proceed with the similarity procedure based one the extracted ontologies. The impact area was estimated by using the toponym reference, as derived from Twitter, as the reference point for the AOV calculation, followed by a viewshed analysis of each Flickr image. Accordingly, in this mode we use Twitter content to orient Flickr data and guide the viewshed analysis.

For the total period of the wildfire incident we identified 10 days in accordance with the dataset we retrieved from the Flickr API. In Figure 5.8 the number of Flickr contributions per each day for the total period of ten days are presented.

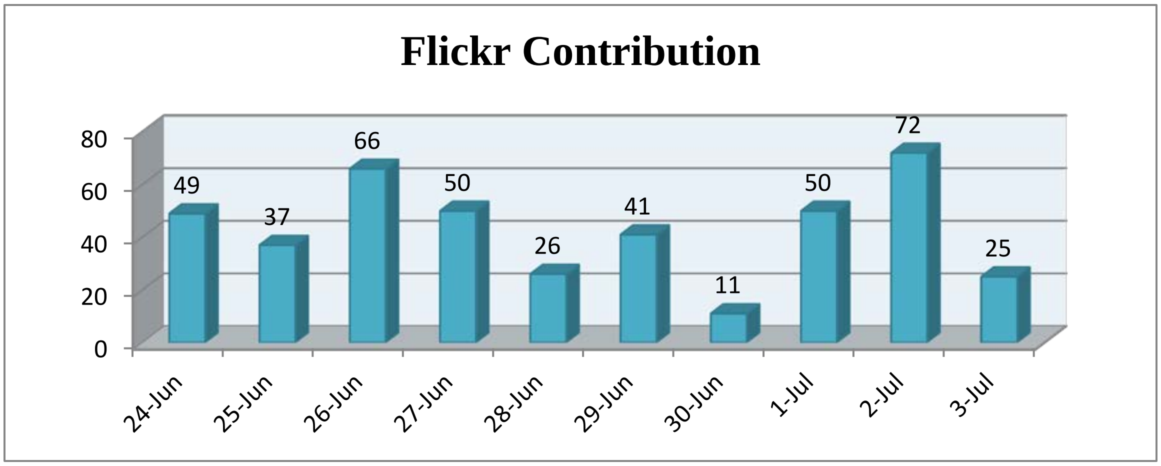

Figure 5.8: Number of Flickr contributions in daily basis for the total period of the wildfire event.

The results of the proposed methodology for the scene modeling based on the Cross-Source Triangulation Framework for each of the ten days are presented in the following figures (Figures 5.9 – 5.18). In each of these figures we present for each significance level range, the resulting impact area of the wildfire as an overlaid raster heat-map, the known wildfire impact area as provided by the US National Oceanic and Atmospheric Administration (NOAA, 2013) following the event as well as the polygon of the city cell area provided by ESRI.

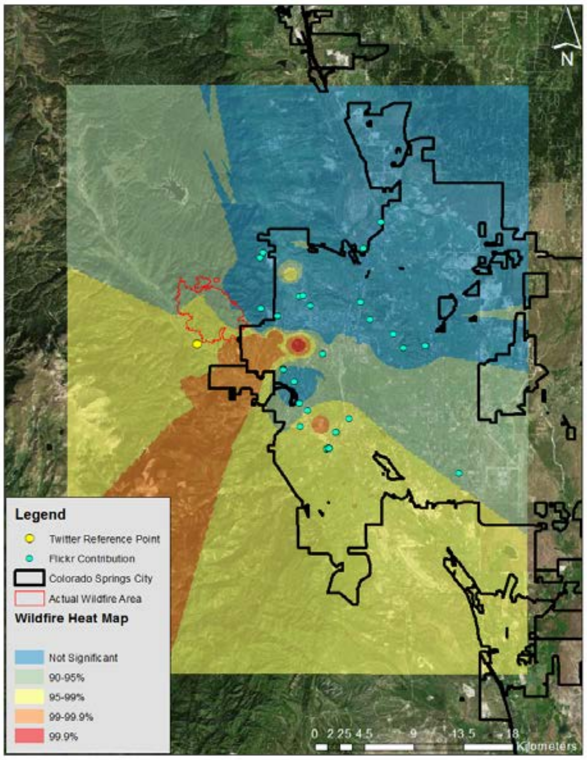

Figure 5.9: Wildfire location assessment for Day 1

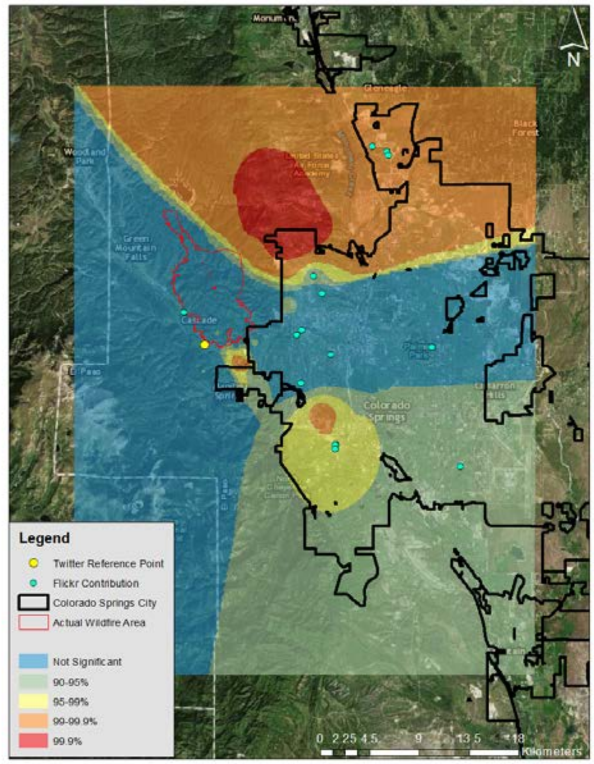

Figure 5.10: Wildfire location assessment for Day 2

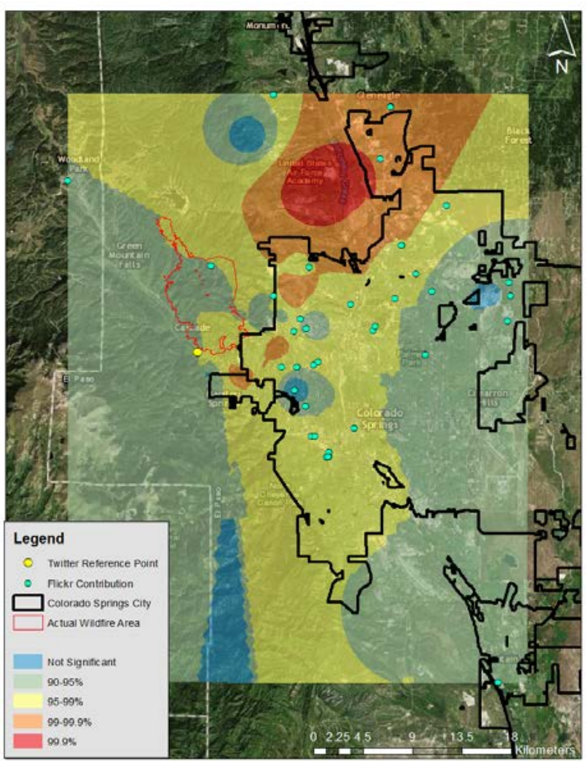

Figure 5.11: Wildfire location assessment for Day 3

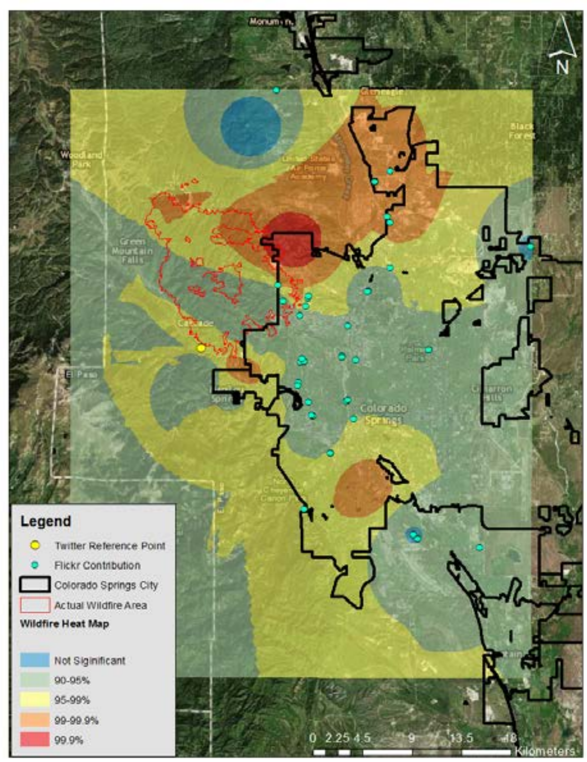

Figure 5.12: Wildfire location assessment for Day 4

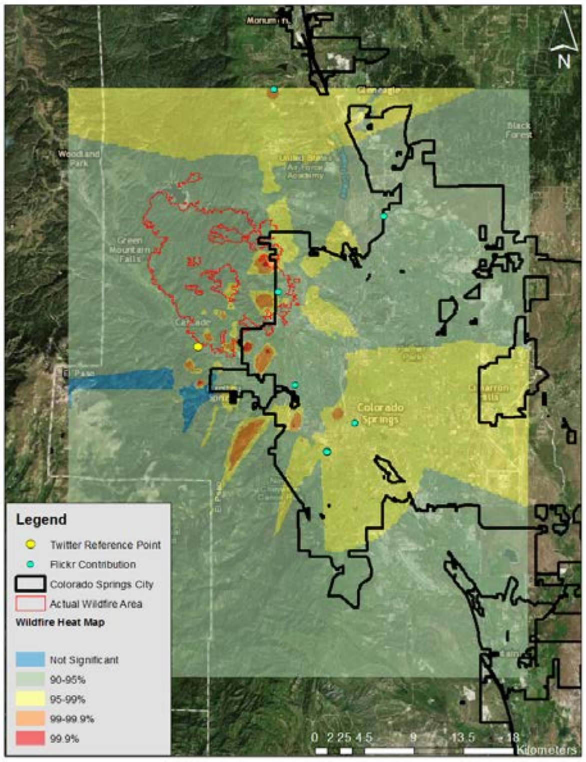

Figure 5.13: Wildfire location assessment for Day 5

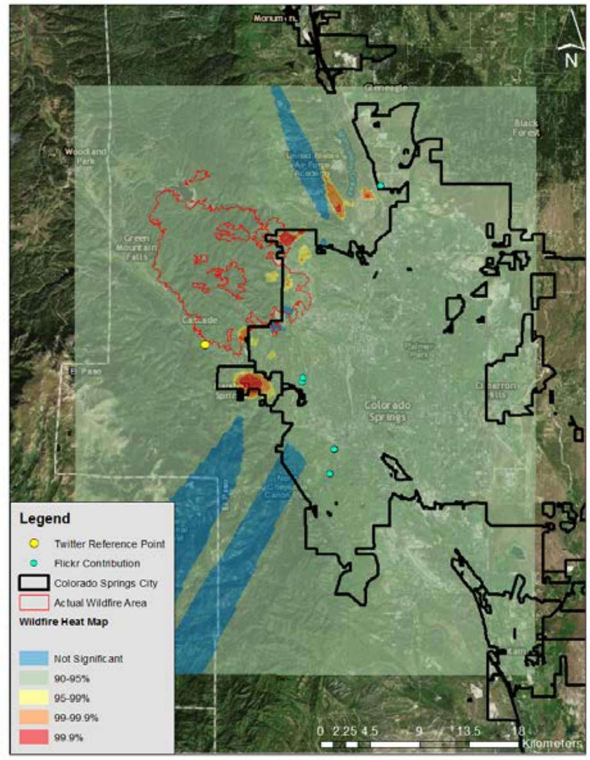

Figure 5.14: Wildfire location assessment for Day 6

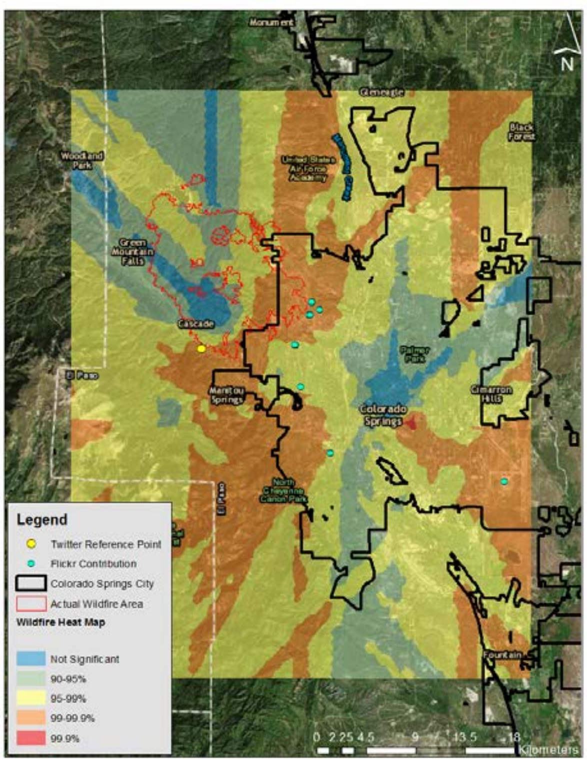

Figure 5.15: Wildfire location assessment for Day 7

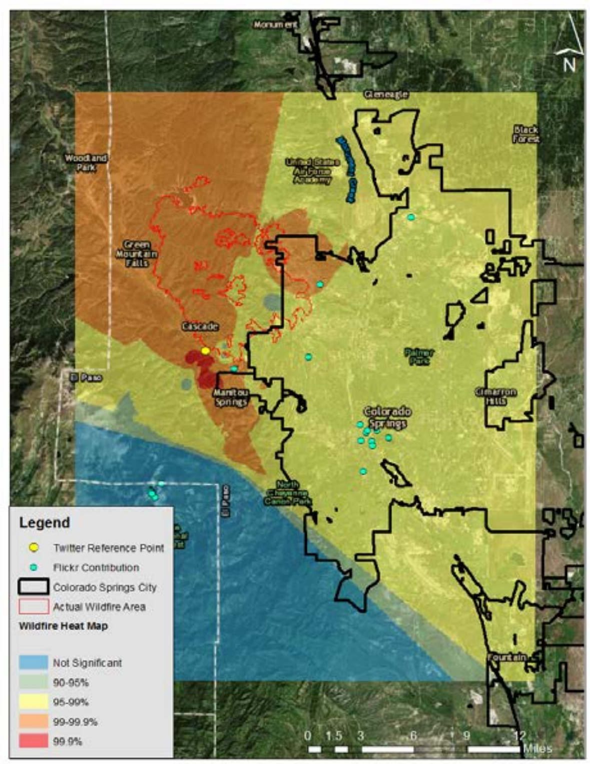

Figure 5.16: Wildfire location assessment for Day 8

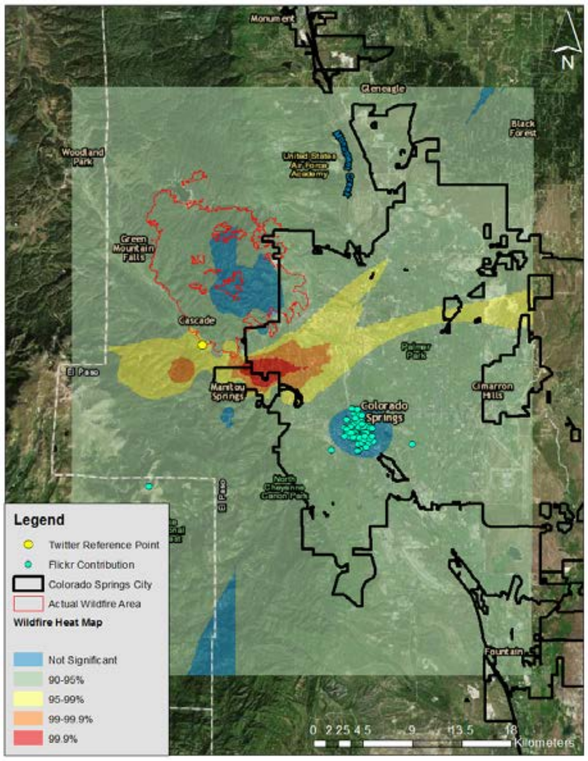

Figure 5.17: Wildfire location assessment for Day 9

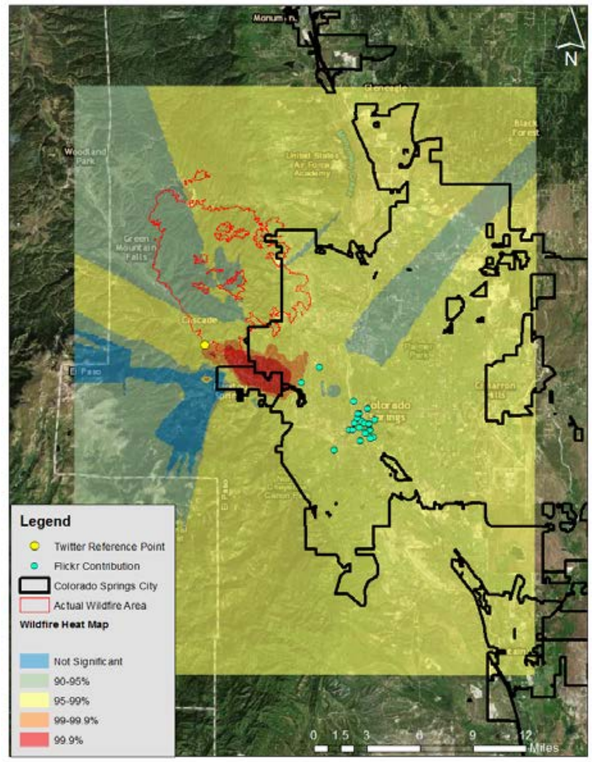

Figure 5.18: Wildfire location assessment for Day 10

After the predicted area/location for each day, which is considered the third component of our ontology, the final step was to examine the proposed methodology of the semantic similarity in order to examine if we can discover and model the patterns in transient scenes. As shown in Figure 5.1, the feature class in this test case will be comprised of three component objects; the actual area of wildfire (Component A), the impacted city (Colorado Springs) (Component B), and the assessed location/area via social media feeds (Component C). Concerning the component C, we consider only the red hot spot for further analysis since the confidence level is 99.9%.

After the collection of the geometries for each of the ten days, we proceed with the extraction of the spatial signatures for all days using the HoF. Given the fact that the ontology in this case is comprised of 3 components, based on *Equation 8*, as it was described in Subchapter 3.4, we formulate three possible pair combinations of the constituted components. In contrast with the application of the proposed framework in the previous chapter (Chapter 4), we apply directly the optimal attribute selection to the extracted spatial relationships before we proceed with the similarity assessment. The final outcome of the similarity scores, as presented in Table 5.1, between the ten days of the wildfire is illustrated in the Figure 5.19.

Table 5.1: Similarity scores for the ten days of Waldo Canyon fire.

	Day 1	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**	**Day 8**	**Day 9**	**Day 10**
Day 1		0.700	0.547	0.545	0.377	0.865	0.557	0.531	0.888	0.815
Day 2	0.700		0.592	0.674	0.412	0.578	0.848	0.829	0.582	0.660
Day 3	0.547	0.592		0.420	0.826	0.435	0.452	0.442	0.441	0.506
Day 4	0.545	0.674	0.420		0.645	0.681	0.775	0.828	0.671	0.860
Day 5	0.377	0.412	0.805	0.584		0.479	0.484	0.475	0.483	0.582
Day 6	0.865	0.578	0.435	0.681	0.479		0.682	0.652	**0.991**	**0.916**
Day 7	0.557	0.848	0.452	0.775	0.484	0.682		**0.962**	0.672	0.741
Day 8	0.531	0.829	0.442	0.828	0.475	0.652	**0.962**		0.644	0.762
Day 9	0.888	0.582	0.441	0.671	0.483	**0.991**	0.672	0.644		**0.926**
Day 10	0.815	0.660	0.506	0.860	0.582	**0.916**	0.741	0.762	**0.926**	

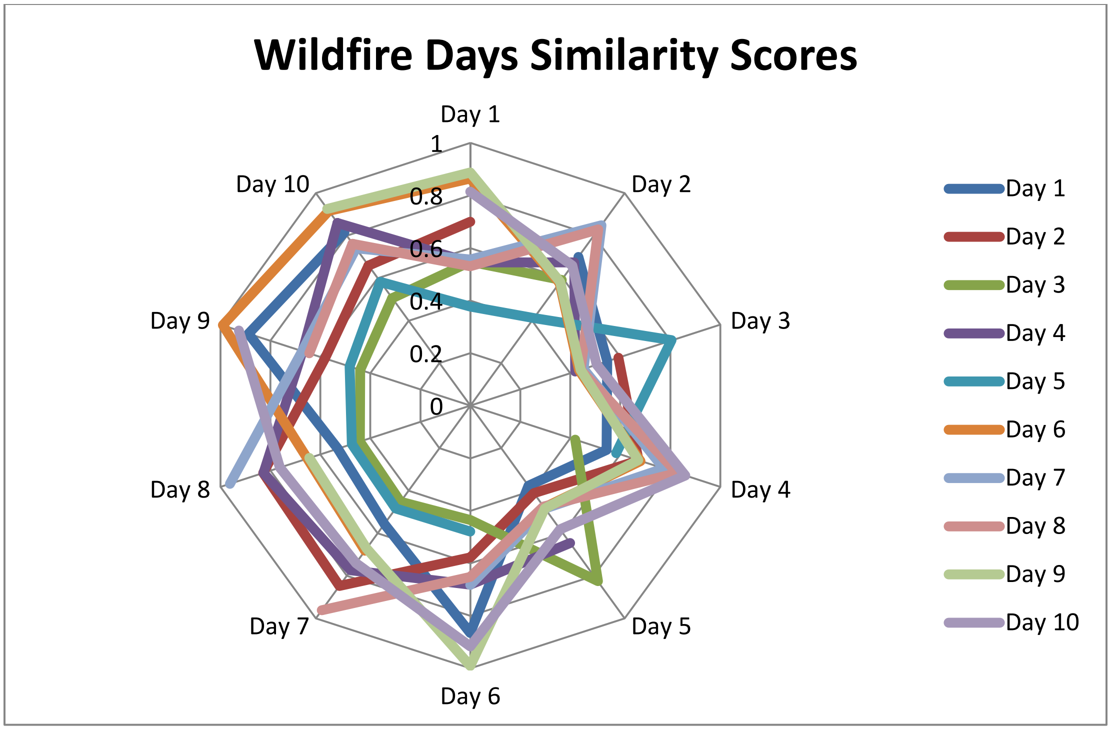

Figure 5.19: Similarity scores for the ten days event of Waldo Canyon wildfire.

Based on the Figure 5.19 it becomes apparent that our proposed methodology is able detect the discernible patterns in transient scene as well. The highest similarity scores (correlation coefficient ≥ 0.9) can be found among the days where the wildfire event is already progressed. The reason behind that is dual; firstly the actual wildfire area concludes in it's final form after Day 5 and secondly the hot spot form the social media feeds is relocating closer to the commercial center of the city of Colorado Springs as well as after Day 5. That realization becomes obvious also by analyzing the similarity results where judging by the above chart the highest similarity scores come from the pairs of days 6 to 9, 6 to 10, 7 to 8, and 9 to 10 while the lowest similarity score was detected in the pair between 1 and 5 as it was expected.

CHAPTER 6: CONCLUSIONS AND FUTURE RESEARCH

6.1 Summary and Conclusions

This research has demonstrated the development and application of an approach to quantify the abstract spatial (topological and directional) relations among object pairs in a scene, and to aggregate this information in a scene description for the purpose of a semantic scene similarity schema. The proposed ontological scene matching uses ontologies for feature classes to guide the selection of metrics, and then group the metrics during scene similarity evaluations. Similarity determinations using the force histograms of fuzzy Allen relationships, the use of NCC, and ontology-guided attribute selection were found to be a robust technique that is able to provide with fast and accurate results. Concerning the used spatial relationship model, it was proven that it is has rich support for defining the fuzzy topological and directional relations and fuzziness in relation's semantics and they can answer the questions that where in space a certain topological relation exists. Abstract and/or fuzzy spatial relations are not depended on metric calculations of the objects, which contribute to the semantic properties of them.

Another advantage derives from the fact that the abstract relations are not dependent on metric calculations of the objects, which also contributes to the semantic properties of them. However, despite this fact, the qualitative measurements are quantified in order to get meaningful similarity results both in spatial configurations in built and transient scenes. Additionally, the benefits from the attribute selection and the reduction of the thirteen relations prove to be essential for the improvement of the classification. This would be even more crucial in cases where the training sets were larger where the dimensionality is increasing.

Concerning the second test case, the analysis of social media content in order to extract geospatial information and event knowledge from such crowd-contributed data has become the subject of substantial research activities. This research demonstrated an approach that makes use of the multimedia nature of social media content by examining the benefits of the complementary use of heterogeneous sources of social multimedia feeds in order to assess the impact of a natural disaster. More specifically, we introduced a novel social multimedia triangulation process that uses collaboratively Twitter and Flickr content in a two-step integrated process. In this approach, we practically crowdsource approximate orientations from Twitter content and use this information to orient accordingly Flickr imagery and identify the impact area through viewshed analysis and viewpoint integration. Combined, these datasets comprise multimedia crowd contributions communicating the event, and complement each other with respect to their thematic content. Beyond the usefulness of this methodology to assess and predict the impact area of a natural disaster, this approach proved to be a robust method for the spatial modeling of more conceptual scenes such as the ones comprised of social media spatiotemporal clusters.

Our objective was to pursue an innovative solution that harnesses these diverse crowd contributions in order to delineate the impact area of this particular event and therefore to enable the spatial modeling of this scene for the purposes of an ontology-driven scene similarity. The two-step approach that we introduced here proceeded by first using Twitter content to identify toponym references associated with a disaster. This information was then used to provide approximate orientation for the associated Flickr imagery, allowing us to delineate the impact area as the overlap of multiple view footprints. This is a two-step crowdsourcing process that crosses platforms and media in order to delineate an event: we use the text in Twitter to crowdsource a compass, in the form of a reference viewpoint, and then use this information to aggregate the views of another crowdsourced dataset, namely Flickr imagery. In essence, this extends the scope of VGI, in that crowdsourced content is not limited to the datasets, but also extends to harvesting information that is critical for the analysis of these datasets too. This approach allows us to bypass computationally intensive image analysis tasks associated with traditional image orientation (e.g. the identification of conjugate features), yet supports the aggregation of multiple image views in order to delineate the impact area as the aggregate of multiple views. The results of our analysis show the improvements in delineating and modeling the impact area through the introduction of such information is feasible.

In overall, this dissertation has proven the research hypothesis test according to which given that a scene is a composite structure, comprising individual key components (e.g. objects) as they are arranged in space, a semantic similarity measure based on abstract spatial relations of these objects by combining topology, direction, and distance can provide us with a more descriptive spatial signature of each scene and better support scene similarity assessment in diverse applications. The proposed methodology managed to identify and compare the discernible spatial patterns both in built and transient scenes and therefore to prove that there is a spatially relevant character behind them that present semantic similarities.

As we are moving towards a wider adoption of crowdsourced content we have to continue being aware that such content is the outcome of a geosocial process: the level of participation, and the patterns of contributions are driven by the particularities of the corresponding physical and social environments. In our particular case, contributions were primarily made from the South and Southeast areas, not only due to the presence of urban areas in them, but also due to accessibility issues and the nature of the event itself. Having had a more broad distribution of contributions around the impact area would have resulted in further improvements. However, even for such adverse conditions as the ones we encountered in this case study we showed that at a confidence level of 95% we can increase the accuracy of the prediction when we use our two-step triangulation-process. This supports the argument that by harvesting various types of information from diverse crowdsourced content we can better infer event-specific information from these citizen contributions.

One thing to consider in conjunction with the level of accuracy is that it would be affected by the granularity of the reference point. For example, if people were referring to the ’Colorado wildfires’, our approach would not be able to generate meaningful results.

Generally, one would reasonably expect a link between the granularity level of event references, as they emerge through public discourse, and the type of the corresponding event. While some events have a rather localized footprint (e.g. wildfires), others have a broader impact (e.g. hurricanes). This can be viewed as an extension of the problem of geo-parsing text at global- and local-scales (Leidner and Lieberman, 2011). Furthermore, the dynamicity of an event may impact the analysis: a fire is a very dynamic event, but was (in this case) still spatially contained. If it were to be spreading across large areas our analysis would have to be segmented across temporal intervals, within which the event would be mapped at distinct instances, and its evolution tracked accordingly. Presumably, this could also lead to the emergence of sequences of toponyms for the same event.

It is worth noting that rather focusing on fine-tuning the accuracy of the outcome of the analysis, our main objective in the second test case was to demonstrate the feasibility of our approach in the context of a rapid assessment of the impact area of an event given non-curated data corpus such as the one presented here and to spatially model a transient scene. As we have shown above, even with certain approximations, e.g. using average camera model values for images without Exif information, we are able to assess the impact area quite well. Such approximations could be further improved and refined by using techniques for estimating missing camera parameters (e.g. Bujnak *et al.* (*2010*) or de O Costa *et al.* (2014)). Similarly, the viewshed analysis can be refined to account for the combined effects of the accuracy of the DEM (e.g. Oksanen and Sarjakoski (2006)) as well as the accuracy of the technique used to calculate it (e.g. Fisher (1993)).

Nevertheless, we need to remain cognizant of the particular nature of social media contributions may result in biases in their patterns of contribution. For example, Li *et al.* (2013) focused on social media usage in Twitter and Flickr, finding a relationship between Twitter usage and well-educated high-income people, particularly white and Asian populations. More relevant to this work, Kent and Capello (2013) studied the use of social media during a crisis situation (a wildfire). Their analysis showed that demographic characteristics of the area impacted by the emergency situation could be used to reveal the propensity of its population to contribute information in social media during such a crisis. These works reveal some of the intrinsic nature of social media contributions as they relate to geospatial information, warranting the further study of such activities in order to gain a better understanding of the value and quality of this crowdsourced content.

In order to overcome the demographics-related limitations (and resulting biases) it is possible to consider active social media approaches, whereby requests for contributions are issued for locations that are underrepresented in the harvested data. This nevertheless would not address the limitations of population gaps, where low population density results in lack of data (thus limiting the accuracy of the analysis). Towards that end, one could consider the integration of social media feeds with traditional geosensor networks, in order to collect from the latter focused information in response to the breaking events that are detected in the former and therefore based on its semantic similarity with the unknown events to enable us with a kind of automated event recognition and characterization. While such integration still remains largely unexplored, it clearly emerges as a promising future direction due to the substantial advancements in social media harvesting and processing.

6.2 Future Work

In order to conclude, with respect the outlook, the experiments indicate that this approach could lead to an ontology-aware scene interpretation module, whereby ontology knowledge can be used to aid scene interpretation and/or the monitoring of a construction progress (assessing whether it is consistent with a specific type of compound structures) for the first case and for event recognition based on the discernible spatial patterns of a known event. This has great potential, as it could enhance traditional object extraction processes with the interpretative knowledge that is traditionally embedded in ontologies and which is typically the summarization of analyst expertise. More specifically the following considerations indicate a strong potential for the usefulness of the proposed methodology in overall for future research directions and applications.

One of the fundamental tasks in image analysis and understanding is the assignment of a geographic object to image objects (Castilla and Hay, 2008). Therefore it becomes critical to devise a scene description methodology, which will enable an image content representation that will comply with the conceptual reality of an interpreter (Lang, 2008). That becomes essentially necessary especially in the case of a conceptual scene where its components are comprised of social media spatio-temporal clusters. In order to achieve a higher scene representation, ontologies coupled with fuzzy spatial relationships can be very valuable since their main functionality is to create the relationships between the objects in the world that are observed, in terms of geospatial data, and the objects created from the spatial analysis (Bittner and Winter, 1999). In other words, this research directions allows the linking between real-world concepts that are rich in contextual information with the content information existing on a spatial scene either static or dynamic; either in a built environment scene or in a conceptual event scene.

Another important consideration is the ability to handle both qualitative and quantitative information as well as to enable the quantification of qualitative information. The latter appears to be a very active research direction nowadays since It is challenging to link the qualitative and subjective knowledge with the quantitative and objective information, which is also refereed to the literature as the bridging of the semantic gap, as was mentioned to Section 2.1. Ontologies appear to be the connecting link between the qualitative, subjective representation of a knowledge expert in a specific domain and the quantitative, objective representation of a scene.

Also a critical issue in the broad field of GIScience that needs to be addressed is that of change since many of the applications incorporate change detection as new geospatial data are acquired continuously. According to Mark *et al.* (2005) although the construction of an ontology of change and geographic processes might address this issue, it is a temporary solution toward constructing the ontological foundations for GIScience. In this manner, although the description of geographic objects of a feature class remains static, an ontology of object identity changes is enables an enriched framework to monitor drivers of changes. An interesting research towards this research direction can be found on the work done by Kauppinen and de Espindola (2011) for the ontological representation of deforestation processes and land change trajectory in the Brazilian Amazon.

In addition, another important factor that we need to consider is the open world assumption versus the closed word assumption concerning the possible interpretations of a spatial scene (Falomir et al., 2011). Let us consider a subject matter expert, analyzing an image using supervised classification techniques where a certain threshold is used in order to classify parts of the scene accordingly. So for example part of scene that exceeds a threshold value of e.g. 0.4, will be classified as type A while the remaining parts will be considered as representative of a class that is neither of type A nor a sub-class of this type. Such a restrictive hypothesis is quite convenient and thus regularly used in traditional hierarchical classifications where the conceptualization of the world is represented as a closed system. Similarly, in the case of the Boolean spatial relations e.g. in RCC, it denotes a deterministic representation which entails certain limitations. On the contrary, ontology engineering and consequently the geosemantics that are based on description logics propose an open world system where anything is true or false unless the contrary can be proved. Therefore the major difference between a closed and an open world assumption that needs to be taken under consideration for future research is a rigorous conceptualization and description of the concepts of interest, by assigning more emphasis on necessary and sufficient conditions in order to enhance the accuracy of the reasoners in classifying the objects correctly.

Finally, the appropriate description and modeling of the vague and fuzzy nature of geographic concepts still remains a very important research direction in GIScience especially nowadays where new geospatial data sources e.g. social media are stressing the need for new approaches in order to appropriately exploit their full potential. As Comber et al., 2005b arguments, much geographic information is an interpretation of reality and that it is possible for multiple interpretations to co-exist. For example, the ‘‘Mount Everest’’ concept might refers to its summit, but there is no clear threshold for which parts of Mount Everest are part of the mountain and which belong to its neighbors (Bittner and Smith, 2001). As Third *et al.* (2007) presented, vague concepts can be integrated successfully in an ontology of vague geographic concepts. The importance of this issue becomes especially critical when the geographic entities that describe a spatial scene are characterized by fuzzy boundaries and therefore by fuzzy relationships between the entities.

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BIOGRAPHY

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In the fall of 2011, he entered the Ph.D. program in Earth Systems and Geoinformation Sciences at George Mason University in Fairfax, Virginia. He was a graduate research assistant with the Center for Geospatial Intelligence where he was supported through projects funded by NGA, IARPA, and Draper Lab. During his Ph.D. studies he also had the opportunity to intern at the World Bank as a GIS Specialist and Data Scientist.