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Detecting and Identifying Collective Phenomena within Movement Data

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

(signature) ....

Abstract

Collective phenomena are ubiquitous in our every day lives; each day we are likely to observe or take part in a collective. Examples include a traffic jam on the way to work, a flock of birds in the sky or a queue in the shop. These examples include only three types of collective that are considered in this thesis: those phenomena whose individual members can be assigned a physical location in geographic space. However, this criterion is satisfied by many different types of collective.

The movement patterns that are exhibited by collectives are one of their most prominent properties; it is often the property that we wish to reason about most. For example, the movement patterns of crowds, traffic or demonstrations. This thesis hypothesises that, given a dataset that comprises the movement data for a group of individuals, the presence of certain collectives can be achieved through an examination of the exhibited movement patterns.

To identify the different types of collective that exist, a general taxonomy of collectives is presented. A class of collectives are found to manifest themselves through spatial coherence. Therefore, a set of spatial coherence criteria have been developed that can be applied to a movement dataset to indicate if any individuals within that dataset may be participating in a spatial collective. To indicate the different types of spatial collective that may be extracted, a taxonomy of spatial collectives is also presented.

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Publications

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1 Introduction

Groups of individuals exist, that for some reason, can be considered as coherent and therefore, at some level of granularity, a single entity. Referred to as collectives, these phenomena are ubiquitous in our everyday lives. Consider a journey to work or to the local supermarket. On the way to either destination you may get stuck in a traffic jam, either as one of many passengers in a car, or on a form of public transport. If travelling by car you may park in a car park. At some point in the day you may be a part of a crowd of shoppers or a queue in the canteen or at the checkout. Each of these groups could be considered to be a collective. It is not just ourselves that participate in collectives. Animals can form part of a herd or flock and plants can form forests. Objects can also be considered to form collectives; for example, the books on loan from a library, the musical instruments that are owned by an individual or, an individual's stamp collection. The existence of collectives is not limited to a particular domain; many, if not all, items can be thought of as a collective at some level of granularity. At a high level of granularity a herd can be considered as a collection of animals; at a lower level, an animal is a collection of tissues and organs. At an even lower level, an organ is a collection of cells which themselves can be considered as a collection of molecules at a lower level.

Increasingly, information systems are required to be able to reason and predict how a collective may behave. For example, the movement patterns of crowds, traffic or demonstrations. Existing work that has focused on specific types of collectives such as crowds [Ali and Moulin, 2005] and carnivals [Batty et al., 2003], appears to focus on the level of the individuals, thus omitting important information about the collective itself. Often, in everyday language, it is the collective itself that we wish to reason about. For example, when we comment on or query the behaviour of a traffic jam, we usually refer to the collective itself. Questions such as 'how long is the traffic jam?' or 'how long were you in that traffic jam' are much more meaningful than examining the movement that is exhibited by all of the cars that are travelling along a congested route. Traffic is only one example – the same can be said of phenomena such as a crowd, a herd of cattle and a forest.

Within the field of applied ontology, there appears to be little agreement on whether such a phenomenon can exist and, if it does, what sort of phenomena collectives represent. For example, some researchers that do believe collectives to exist state that they must have at least two members [Bottazzi et al., 2006], whereas others allow singleton [Bittner et al., 2004] or even empty [Rector et al., 2006] collectives. The research presented within this thesis, has indicated that a wide range of different collectives exist across multiple domains; if information systems are to be capable of reasoning about collectives, they should be able to distinguish between these different types.

The movement patterns that are exhibited by collectives are one of their most important properties. An increase in the availability of technologies that can track individuals has led to a growth in the number of movement (i.e., spatiotemporal) datasets. Such datasets could record multiple trips made by one individual or the movement of multiple entities. Movement pattern analysis can help identify more meaningful information about the individuals and objects whose movement patterns have been recorded. If the movements of multiple entities have been recorded, it is possible that a collective could exist in that dataset; movement pattern analysis could allow information systems to identify the presence of that collective. There are many applications for a system capable of identifying collectives within a movement dataset including traffic monitoring and management, security, geographical information systems and the prediction and reasoning of animal behaviour.

1.1 Aims

The aims of this thesis are to:

- clarify the possible meanings of *collective* and determine the different types of collective that exist;
- construct a general taxonomy of collectives;
- identify and characterise spatial collectives as opposed to general collectives;
- develop a method for identifying collectives within a movement dataset (i.e., a spatiotemporal dataset);
- propose an updated taxonomy which deals only with spatial collectives – this taxonomy could be applied to the collectives that have been extracted from a dataset to indicate their type.

1.2 Novelties

To the best of my knowledge, the following features of this thesis are entirely novel.

- A review of existing research has established that there appears to be no framework that is capable of handling and distinguishing the wide range of collectives that exist. Therefore, a taxonomy is presented that allows collectives to be classified according to five criteria: membership, location, coherence, depth and role.
- A subset of collectives have been identified that manifest themselves through spatial coherence and therefore, by using movement pattern analysis can be identified within a dataset.

- A method has been developed that identifies the presence of these collectives, referred to as *spatial collectives*, within a dataset and the individuals that are participating in that collective. This method has been implemented and tested on two datasets.
- A new framework has been identified, the Three-Level Analysis (TLA) framework, that allows collective motion to be accurately represented and analysed.

1.3 Thesis Structure

A prerequisite to identifying the presence of collectives within a movement dataset, is to understand what type of phenomena they are and the different types that exist. Whether or not collectives exist and, if so, what they comprise are both ontological questions. Chapter 2 gives an overview of the treatment of collectives within the field of applied ontology.

The results of the research presented in Chapter 2 indicates an apparent lack of agreement on what what type of phenomenon a collective is and what properties it may have. Therefore, clarification is given in Chapter 3 of what the term *collective* will refer to within the research presented here. Within the existing research there appears to be no attempt to examine and classify the different types of collectives that exist across the various domains. Although these collectives will have some differences they also share some common properties which, when used in combination, may allow the different types of collectives to be distinguished. These properties form the basis of a general taxonomy of collectives that is presented in Chapter 3.

The general taxonomy of collectives highlight the wide range of collectives that exist but it is unclear whether they could all be identified within a movement dataset. Chapter 4 analyses suitable existing methods within movement pattern analysis that could allow the presence of a collective to be identified. The review is split into two components: definition and extraction but also considers visualisation methods and issues such as granularity.

The review of movement pattern analysis research relating to collectives reveals concepts and methods that could possibly be extended to apply to the general class of collectives. However, no method is identified in Chapter 4 that allows the full range of collectives to be identified within a movement dataset. Reflection indicates that it may not be possible to identify all of the collectives outlined in Chapter 3; therefore, *spatial collectives* are introduced in Chapter 5: a group of collectives that manifest themselves through spatial coherence.

The different forms of spatial coherence that could be exhibited by spatial collectives are identified and a set of *spatial coherence criteria* presented that can be applied to a dataset and highlight a group of individuals that may be considered a spatial collective.

To evaluate the coherence criteria, a computer program has been developed which allows the specified coherence criteria to be applied to a movement dataset. Chapter 6 outlines this computer program. Two datasets are used in the evaluation of the coherence criteria: a synthetic dataset and a real dataset; the real dataset records the movement of ships located within the Solent over a twenty-four hour period. Chapter 7 details the application of the criteria to the two datasets.

The method proposed in Chapter 5 only identifies spatial collectives, a subset of the full range of collectives outlined in Chapter 3. However, it is unclear what types of spatial collective exist. The general taxonomy could be applied to the groups identified, but since it covers a wider range of collectives, some of the criteria within the taxonomy are found to be irrelevant and others need expanding. Therefore, a taxonomy of spatial collectives is presented in Chapter 8.

Chapter 9 discusses and evaluates the work presented within this thesis to establish whether the original aims have been satisfied leading to the conclusions that are found in Chapter 10.

2 The Treatment of Collectives in Applied Ontology

If the type of collective is to be identified, the different types of collective must be established along with the relationships that exist between them; this research could form a taxonomy of collectives. A prerequisite to developing such a taxonomy is to define and understand exactly what is meant by the term *collective* and the kinds of phenomena that one is trying to represent and reason about.

Whether or not collectives exist and if so, what they comprise, are both ontological questions. Ontologies provide a framework to formally represent and reason about the world that we live in. Often an ontology will focus on a subset of this world (i.e., a particular domain); examples include biology, chemistry, medicine, geography and social science. Although there is an increasing need for ontologies to reflect the world that we live in, many ontologies do not appear to represent collectives as we think of them in our day-to-day lives (i.e., as single *unities*). This Chapter will examine the treatment of collectives within the field of applied ontology, the definitions that have been given and the representation methods that have been proposed. Specific ontologies will be examined first (section 2.2), followed by more general theoretical research (section 2.3).

2.1 Terminology

Before reviewing the treatment of collectives within existing ontologies, it is important to understand the terminology that will be used.

Endurants and *Perdurants*

- Endurants (or *continuants*) are entities that endure through time. They may lose or gain parts but, at each and every time that they are present, they are 'fully present'. In contrast, perdurants (or *occurrents*) persist in time: at each time instant that they are present, they are only partially present [Smith et al., 2006]. Masolo et al. [2003] distinguish between these two types of entity according to their ability to exhibit change: an endurant retains its identity through time and therefore, can be said to exhibit change but the parts of a perdurant do not retain their identities and therefore, cannot be considered to change. An example of an endurant is this thesis; the process of reading the thesis is a perdurant.

Universals and *Particulars*

- Universals and particulars can be distinguished using the relation of *instantiation*: if an entity can have instances it is referred to as a universal, but if it cannot, it is a particular. Traditionally, proper nouns and 'common nouns' are used to denote particulars and universals respectively [Masolo et al., 2003]. For example, prime minister and poet are both examples of universals; David Cameron and John Keats are both particulars.

Intensional or *Extensional*

- A collective could be defined in intension or in extension. If defined extensionally, the collective is defined by its members and must have those specific members in order to exist. For example, the original members of the pop group The Beatles is a collective comprising John Lennon, Paul McCartney, George Harrison and Ringo Starr. In contrast, the members of an intensionally defined collective all satisfy a particular criterion and therefore, may not be the same throughout the collective's lifetime. The Bournemouth Symphony Orchestra and the British Computer Society are both examples of collectives defined in intension. Whether a collective is extensionally or intensionally defined is not always clear; further discussion on this point can be found in section 3.2.1.

2.2 Specific Ontologies

A number of ontologies include a notion that relates to collectives. However, the treatment of these phenomena vary between the different ontologies.

2.2.1 Descriptive Ontology for Linguistic & Cognitive Engineering (DOLCE)

DOLCE (Descriptive Ontology for Linguistic and Cognitive Engineering) has been developed as part of the WonderWeb Foundational Ontologies Library. As the name suggests, it has a cognitive bias [Masolo et al., 2003]; it tries to 'capture the "ontological categories" that underlie' natural language and human common sense [Wood and Galton, 2009b]. The ontology is limited to particulars; universals appear in DOLCE as a way of characterising and organising the particulars, but they are not considered part of the domain of discourse – they are thought of as being 'formally separate'. Although collectives are ubiquitous in the way we commonly conceive our world, and can easily be considered particulars, DOLCE appears to offer little support for them. The categories of *Agentive Physical Object, Non-Agentive Physical Object, Social Agent* and *Non-Agentive Social Object* could all be used to represent almost any individual member of a collective, but there is no category that directly replicates the concept of a collective.

A set of basic 'leaf' categories form the basis of DOLCE. Since 'incompatible essential properties' can be ascribed to co-located objects, it is assumed that they are different and, therefore, that co-location in space is possible (i.e., DOLCE adopts a multiplicative approach). A popular example is the problem of a vase and the clay that it is made of. A multiplicative approach would state that although related, these two entities are different: 'the vase is constituted by an amount of clay, but it is not an amount of clay' [Masolo et al., 2003] – the vase will cease to exist if its shape radically changes, this is not true of the clay.

The top-level classes of DOLCE are *Endurant*, *Perdurant*, *Quality* and *Abstract*. *Set* is included as a sub-category of *Abstract*; however, a set cannot identify a collective (section 3.1.1). A set is an abstract entity - it has no temporal or spatial 'qualities'. Within the class of *Endurant* is the subclass *Arbitrary sum*. 'My left foot and my car' are given as an example of this subclass. This could be seen as an example of a purely fiat collective (i.e., it has been deemed a collective solely by an external agent). However, this does not seem to do justice to collectives which are not fiat, for example, those that are considered a collective due to a purpose such as a football team or an orchestra. Arbitrary sum is considered as a sibling of the classes *Physical Endurant* and *Non-Physical Endurant*. The former would seem a sensible place to have a category that represents collectives; however, no such class exists. The subclass *Amount of matter* could be deemed suitable for some collectives, examples given by Masolo et al. [2003] include 'some gold' or 'some cement'. However, these are only a small subset of the range of collectives that exist. The category *Amount of matter* refers to endurants that have no unity; their identity changes 'when they change some parts' – they are *mereologically invariant*. This would not be suitable for collectives whose members can change without the identity of the collective being affected (e.g., a football team).

A set of 'primitive' relations are defined within DOLCE, some of which could be used to model the relationship that exists between a collective and its members. Two forms of parthood relations are defined: one that is 'a-temporal' (*parthood)*, and one that is 'time-indexed' (*temporary parthood)*. Temporary parthood holds for endurants and can either be *mereologically constant* or *mereologically invariant*. If an individual is only a member of a collective for a short time, temporary-parthood could be used to represent the relationship (e.g., within a waiting list).

Two other relations that are of relevance are *dependence* and *participation*. Participation is said to occur when an endurant is 'involve' in an occurrence. The relation is time-indexed and can be split into *temporary participation* and *constant participation*. DOLCE defines participation as a relation between endurants and perdurants and, therefore, if it is to be used to represent the relation between a member and a collective, the collective would have to be viewed as a perdurant. Although suitable for some types of collective, where an individual can be considered as participating in the collective, (e.g., 'dynamic collectives' proposed by Galton [2005]) viewing a collective as a perdurant does not always seem intuitive and could not allow the full range of collectives that exist to be represented.

For some, a collective is considered to depend on its members [Niles and Pease, 2001; Bittner et al., 2004], thus suggesting the relation *dependence*. DOLCE defines two forms of this relation: *specific* and *generic constant dependence*. Both relations apply to properties but the former could also be applied to particulars. Constant dependence could be used for collectives which are defined in extension (i.e., they are defined by their members and therefore, must have specific members in order to exist); however, what about those collectives that can change members but retain their identity such as a queue or a forest?

2.2.2 Basic Formal Ontology (BFO)

Our world can be viewed in two ways: (1) as comprising endurants, or (2) as comprising perdurants. These two types of entity exist differently, especially with respect to time, but could also be considered as complementary. If a framework is to be developed to accurately represent reality both of these views need to be unified whilst continuing to do justice to them both. Therefore, the Institute of Formal Ontology and Medical Information Science (IFOMIS), at the University of Leipzig, has developed a formal ontology BFO, that comprises two sub-ontologies: SNAP and SPAN. The former represents endurants and the latter perdurants. The main focus of BFO is to provide 'a genuine upper ontology' that can be used to support domain ontologies that have been developed for scientific research [Spear, 2006]. Therefore, relations and entities should be represented as if they exist in a 'mind-independent' world [Spear, 2006]. Similarly to DOLCE, there is no distinct class to represent collectives, but, in a way BFO could be considered more friendly to the notion of these phenomena due to the categories that it includes.

More than one source exists regarding BFO [Grenon and Smith, 2004; Spear, 2006], each of which appears to be slightly different. Originally included within the SNAP ontology amongst the class of *substantial entity* were *fiat parts* and *aggregates of substances*. 'Aggregate substances are mereological sums comprehending separate substances as parts' [Grenon and Smith, 2004]. They can be scattered and therefore, do not necessarily have connected boundaries. This category could be used to represent collectives: Grenon and Smith [2004] note that what may be observed as an aggregate at one level of granularity could be viewed as a substance on another. They give as an example a 'collection of soldiers' forming 'an infantry battalion'. However, this category does not allow different types of collective to be distinguished.

Spear [2006] appears to present an updated version of BFO. The original top-level distinctions within the SNAP ontology between *substantial entities* and *SNAP dependent entities* have been replaced respectively with *independent continuants* and *dependent continuants*. Within the category of independent continuant is the sub-category *object aggregate* which represents independent continuant entities that are mereological sums of their separate objects. Spear [2006] gives examples of 'a collection of bacteria' and a 'flock of geese'. Aggregates are defined as 'continuants that are collections of other separate objects'. These are the types of phenomena that could be considered as collectives. However, the location of object aggregate within the SPAN ontology raises the questions of how the identity of an aggregate can be maintained over time. As noted by Wood and Galton [2009b], BFO is 'compatible with' two different views of an aggregate x:

- 'There is some set of objects X such that, at any time t, x exists if and only if all the members of X exist, and at that time x is the aggregate of those members.'

- 'At each time t at which x exists, there is a set of objects X such that, at t, x is the aggregate of the members of X, it being allowable that at different times x is the aggregate of different sets of objects.'

It is specified that, through loss and gain of qualities and/or parts, an *object* can maintain its identity within BFO. Since what appears to be an aggregate on one level can appear as an object on another, it may seem sensible that the second option found above could be taken. However, this is an issue that does not seem to be documented within BFO.

The relations used within BFO correspond to those that are found in mereology. If a collective is to be represented as an aggregate, the members of that collective must be parts of the aggregate. The parthood relation, when used for aggregates, could represent an arbitrary part which, in general, will not be one of the parts contributing to the sum. Therefore, a member of a collective cannot be identified using parthood of an aggregate – when considering a crowd, it is the individual people that you wish to consider as members, not arbitrary parts such as their hands or heads. No other relations are documented that could be considered more suitable to model this membership relation.

2.2.3 Suggested Upper Merged Ontology (SUMO)

Suggested Upper Merged Ontology (SUMO) is an upper level ontology that has been developed via the merging of 'publicly available ontological content' [Niles and Pease, 2001] including John Sowa's upper level ontology [Sowa, 2000]. The top level of SUMO contains all of the high level concepts produced by the merge. Within this layer, objects are split into those that are self connected and those that comprise 'disconnected parts'; the latter are referred to as *collections*.

Each part of a collection is represented using the relation *member*. Collections can gain and lose members without their identity being affected but empty collections are not possible. Collections must be physical; the initial distinction within the top level of SUMO is between physical and abstract entities. Sets are considered a sub-category of abstract but also to subsume classes: sets whose members satisfy a particular criterion. Unlike collections, classes cannot change their members. A category *group* has been included as a sub-category of collection; this subcategory denotes groups of intentional agents.

The distinctions outlined here do appear sensible but, as with the other ontologies that have been reviewed, it does not seem possible to distinguish between the wide variety of collectives that exist within our world. It is possible to distinguish between collections whose members are intentional agents and those that are not, but what about the further possible distinctions within each of these two groups? For example, collectives of intentional agents which have come together due to a common purpose (e.g., an orchestra), and those who have come together to fulfil individual purposes (e.g., a queue).

2.2.4 Intentional Collectives

There is much literature which debates the existence of collective intentionality but instead of adding to this debate, Bottazzi et al. [2006] examine the concept of an *intentional collective*. Although the focus of the work presented by Bottazzi et al. [2006] is on a specific subset of collectives, and some of the distinctions that they make are unclear due a lack of illustrative examples, they do present some interesting ideas and definitions that could be applied to a more general class of collectives.

An extension for existing ontologies is suggested which allows for the representation of collections. Two existing ontologies are used to build this extension: DOLCE and D&S [Gangemi et al., 2004]. Originally developed as a tool that allowed foundational ontologies such as DOLCE to be extended, D&S (Descriptions and Situations Ontology) distinguishes between *descriptions* and *situations*. The former is 'a social object which represents a conceptualization' (e.g., plans and laws); the latter is 'a particular which represents a state of affairs'. An object is defined as social if it is an 'immaterial product of the community' (i.e., the object depends on intentional agents for its existence), and, its 'constitution involves a network of relations and interactions among social agents' [Bottazzi et al., 2006]. It is assumed that the components of a situation form part of an ontologie's domain 'by virtue of a description' and therefore, a situation must satisfy a description. Examples of situations that relate to the examples given of descriptions (i.e., plans and laws), include a plan execution or a legal case.

Bottazzi et al. [2006] distinguish between two different entities: *collections* and *collectives*. Collections are considered to exist in time and be 'localized' – this is in contrast to a set which is considered abstract. Members must be endurants but they 'cannot be parts of the same endurant'; membership is denoted using a *constitution* relation – at any time a collective is regarded as constituted by the set of its members at that time. For a group of individuals to be considered a collection, they must have at least two members which satisfy a 'unity criterion'. Therefore, a collection will depend on at least one social object: once these social objects stop being applied to the collection, the collection ceases to exist. If all of the members of a collection have the same 'leaf type' (determined by the ground ontology), the collection is said to be homogeneous. The definition of collection is used to define the focus of the work presented by Bottazzi et al. [2006], *collectives*: collections which comprise only intentional agents; this is much more restrictive than the notion of collective that is adopted within this thesis.

Collections are seen as social or cognitive objects that depend on the roles played by their members. As Bottazzi et al. [2006] note, this can lead to 'peculiar' space-time behaviour. Collections can participate in processes or actions 'on a member basis', or 'on a whole basis'. An example given is a herd stepping on a person; the person recognises the herd as stepping on them (i.e., on a 'member-basis'). Another example would be a firing squad, where no responsibility is placed on individuals, but on the firing squad as a whole (i.e., 'on a whole basis'). The 'space-time of a collection is the maximal space-time of the members when they are classified by some selected role(s)'. Therefore, if a collection participates on a 'whole-basis' the 'member-basis' will also hold.

Typologies of collections and collectives are presented within Bottazzi et al. [2006]. Since the main focus is on collectives, only a basic typology of collections is given which contains four types: 'simple', 'maximally generic', 'parametrized' and 'organised'. These four different types of collection have been distinguished according to the roles played by the members. A simple collection such as the collection of all trumpets, has only covering roles (i.e., a role(s) that is shared by all members) whereas a maximally generic collection (e.g., a collection of objects that have been chosen at random), need only consist of conceivable objects (i.e., no covering roles are required). The members of a parametrized collection all 'have a quality constrained by some parameter that is a requisite of their covering role(s)'. An example given by Bottazzi et al. [2006] is a crowd of people; the people are considered as a collection due to their spatial proximity. Within an organized collection, the members can be further characterised by the role that they play (e.g., a committee).

The definitions and typology given for collections is used as a basis for a definition and typology of collectives. Bottazzi et al. [2006] consider collectives to be more than collections since they consist of intentional agents: physical or social objects that can conceive descriptions. When agents form a 'unifying plan' they cause the creation of a collective. As with collections, 'collectives are characterized by roles and eventually unified by some description' [Bottazzi et al., 2006]. The typology of collectives is based upon the presence and structure of the plan that unifies the collective; the criteria that the typology is built upon examines the type of plan, how the plan was conceived and its prior existence, whether there is more than one plan and how it is adopted by members of a collective.

A distinction is made between simple and organized collectives in a similar way to simple and organized collections. However, as Bottazzi et al. [2006] note, the source of collective action must be considered to further classify collectives and in particular the plans. Conceived by a cognitive agent, 'a plan is a description that represents an action schema'; the schema will comprise at least one task, one role and one goal. Two types of collective are defined according to their unifying plan: *simple planned collectives* and *intentional collectives*. Within the former, the roles that are played by the members cover the collective in the sense that each member plays them, whereas the latter will always have agents as members which can act on a unifying (maximal) plan which define the roles that are used to characterise the collective. An example given of a simple planned collective is a group of people who all run to a common shelter due to sudden rainfall; a football team 'executing a pass play' is given as an example of an intentional collective. A *maximal unifying plan* can be *negotiated* or *conflicting* resulting in the definition of *stable* and *unstable* collectives. Stable intentional collectives have negotiated maximal unifying plans (e.g., an agreed contract between a customer and a vendor), whereas an unstable intentional collective will have a conflicting maximal unifying plan (e.g., a disagreement between two groups of how to achieve the goal).

Bottazzi et al. [2006] note that the need to distinguish between intensionally and extensionally defined collectives is illustrated when considering the behaviour of a unifying plan with respect to the collective. A plan can be *devised* (i.e., underlie the collective) or *emerging*. An emerging collective will temporarily not be unified by a plan; it is at this stage equivalent to an extensionally defined collective – a contrast to a collective where a plan has been devised and therefore, can be considered as intensionally defined. An example of an emerging collective is when a collective suddenly adopts a new plan thus forming a new collective. These types of collective (i.e., emerging collectives), could be *causal* or *spontaneous*. The former occurs when a unifying plan has a minimum of two 'subplans' that have been 'conceived by different agents who neither conceive their respective plans, nor the unifying plan' (e.g., a group of friends meet in a bar even though it was not planned to do so). Although one agent will conceive the unifying plan, it is usually conceived after the collective has begun to exist. The conceived subplans within a spontaneous collective will usually have started to be conceived by agents at the same time as the collective begins to emerge (e.g., a group of drivers all stop at the same service station because of a storm).

Further distinctions are made between the different types of collective by looking at the relationship between agents and how these agents share the conception of a unifying plan. A *figure*, or *social individual*, is a social object that is defined by descriptions. Examples given by Bottazzi et al. [2006] include organisations, sacred symbols and political-geographic objectives. An *agentive figure* can conceive a plan (i.e., there is an agentive physical object that can act for the figure such as a delegate or a representative). *Maximal agency collectives* are a type of intentional collective where the '(reification of the) maximal set of agents' 'act for a figure'; an example given is the maximal set of employees of Apple. Collectives may be governed or ungoverned: if governed the collective has an agent as a member which 'controls the collective by means of a plan or a metaplan' (e.g., the crew of a vessel). A distinction is also made according to how many members of a 'collective share the conception of its unifying plan'. In this respect, collectives can be transparent (e.g., a group of individuals plan a trip), opaque (e.g., a group of friends organise a surprise party for one of the group), or obscure (e.g., ' collective of agents in a security network').

Within intentional collectives, the way a plan and information are communicated and shared is an important way to distinguish between the different types of collective. Bottazzi et al. [2006] enumerate three possibilities: goal sharing, adoption sharing and trust sharing. An example of a *transparently embracing collective* is given as 'an intentional collective whose members have all adopted the conceived (maximal) plan'. In contrast, a *transparent trustful collective* 'is an intentional collective whose members all trust the conceived (maximal) plan'; an example given is a group of friends who leave for a common destination knowing that all of the necessary resources (e.g., directions, fuel) are in place. Bottazzi et al. [2006] note the need for the social relationships to be considered, in particular how unifying plans are internally structured; however, no examples are given or enumerated in the typology.

All criteria discussed so far relate to properties of the members. Some criteria are found which are based on the properties of the collective when considered as single entities.

However, only one property has been discussed – whether the unifying plan specifies a schedule for the collective then the collective can be said to be *temporary.*

2.2.5 Others

Cyc [Cyccorp, 2011] includes the categories *collection* and *group*. The former is used to denote a class or type. It is noted that a collection differs from a mathematical set since the members of a collection will all have at least one common attribute (i.e., an 'intensional' quality') – sets can have arbitrary members. However, a collection need not have spatial or temporal properties. Two collections can have the same members but not be considered identical since two collections could be defined by two different common attributes.

A group is a collection of objects that, unlike a collection, has temporal and possibly spatial properties. The individual events or objects that make up these 'composite objects' are denoted using the predicate *groupMembers*. Although a collection may be empty, a group must have at least one member. Cyc also defines the category *mob* to refer to groups that have a large number of members which are all of the same type. Examples given of mobs include: a Galaxy ('a mob of stars') and 'a cupful of sand' ('a mob of grains of sand').

Not all ontologies include the notion of a collective. Developed by Onto-Med, the General Formal Ontology (GFO) is a 'component of the Integrated System of Foundational Ontologies (ISFO) that has been designed primarily for biological, medical and biological applications [Herre et al., 2006]. The ontology has three layers: a top level, a core level and a basic level; the first two are abstract. Unlike in SUMO [Niles and Pease, 2001], sets are not considered as a high-level category but, instead, associated with the 'top level of GFO'. The relations *membership* and *identity* are adopted from set-theory. However, collectives are not the same as sets. There appears to be no consideration for collections or groups within GFO.

2.3 Theoretical Work

So far, the treatment of collectives within specific ontologies has been considered. However, work has been carried out within the field of applied ontology that looks at the notion of collectives specifically, namely Bittner et al. [2004] and Rector et al. [2006].

2.3.1 An Axiomatic Theory of Relations

Different terminology systems exist in the domain of biomedicine: the Foundational Model of Anatomy (FMA), GALEN and the Unified Medical Language System (UMLS). Ontologies like the Gene Ontology (GO), must be correlated with each of these systems but, if this correlation is to take place, the different 'fundamental ontological relations' that each of these systems use must be aligned. Bittner et al. [2004] consider six of these relations: *is-a*, *instance-of*, *part-of*, *membership*, *partonomic inclusion* and *partition-of*.

The focus of the work presented by Bittner et al. [2004] is on 'independent endurants': entities that can undergo change whilst retaining their identity. Three different types of entity are presented, each with different temporal properties: *individual endurants*, *endurant universals* and *collections*. A key distinction between these entities is that the first two can gain and lose parts and instances respectively, whereas a collection is considered to be defined by its members and therefore cannot gain or lose any members. Bittner et al. [2004] discusses and formalises the ways in which the three types of entity can be related using the six foundational ontological relations resulting in the presentation of an 'axiomatic theory'. This thesis will focus on collections and the relevant relations: *member-of*, *extension-of*, *partition* and *partonomic inclusion*.

Two types of collection are considered: partitions of individuals and extensions of individuals. In order for two collections to be considered identical, they must have the same members. Collections cannot be empty but Bittner et al. [2004] do allow singleton collections (i.e., collections consisting of only one member). An example is given of a collection p that is comprised of a single member Fred. Bittner et al. [2004] note that p is not identical to Fred since, Fred is a human being with parts that can change over time – this is not true of p. Although Bittner et al. [2004] state that a collection is defined by its members and therefore, cannot gain or lose members, three relationships are defined that allow a collection to be considered as 'fully-present', 'partially-present' or 'non-present' according to if all, some or none of its members exist at a given time. Since a collection must have at least one member, 'full-presence is a special case of partial presence'. An example is given of the collection of cells in a particular individual's body at a particular instant of time. It is stated that the collection cannot cease to exist since it is 'an atemporal entity' but after certain time intervals the collection will be fully-present, partially-present or non-present.

Membership is used to denote when an individual is a member of a collection, and is represented using $\in$. The extension-of relation ties collections to universals. The relation does not hold for all collections (e.g.,'the collection of cells in your body'). A universal will have a maximum of one extension at any given time but need not at every time have an extension (e.g., an extinct species). If a universal has an instance at a given time, then there is a collection that is the extension of that universal at that time.

The individuals within some collections may overlap (e.g., a collection that includes an individual's body and heart). However, some collections will comprise individuals that are 'pair-wise disjoint' at a given time. Therefore, Bittner et al. [2004] define a collection as *discrete* if none of its members overlap and the collection is fully-present. Collections need not be fully present and discrete, or non-discrete, for their entire existence. Bittner et al. [2004] notes the example of a pair of 'Siamese twins before and after separation'. A partition is defined as a collection that comprises 'disjoint parts of an individual y which jointly sum up to y' – the collection is a partition of y. A collection p will partition an individual y at t if: 'the members of p jointly sum up to y at t'; the collection is fully present at t; and, p is discrete at t. It is noted that many partitions comprise fiat parts. If two individuals are disjoint, they cannot overlap.

2.3.2 Collectivity

Within the biomedical domain, it is important that different levels of granularity and scale can be represented and discussed (e.g., from molecular to cellular, or from organisms to ecology). However, often the terms *granularity* and *scale* are not clearly defined. Rector et al. [2006] define two distinct notions that they believe are often confused with granularity: *collectivity* and *size range*. The former refers to the 'degree of collectivisation' and the latter 'the size of an object with respect to the phenomena that affect it'. Rector et al. [2006] believe that such notions could help handle some of the 'troublesome issues' that exist within the domain and therefore, wish to define a 'set of broadly applicable principles' regarding collectives. In particular they wish to distinguish the necessary parthood relations and represent patterns and 'other emergent properties' that relate to collectives.

Rector et al. [2006] argue that *collectivity* and *size range* should be considered as two distinct dimensions. The effect of a collective is 'a function of the individual effects'; however, sometimes it is not possible to predict the collective effect even if the individual effects are known; it is traditional to refer to such effects as *emergent*. An individual on one level can be considered as a collective at a higher level with 'emergent properties'. There are properties and effects that can be ascribed to a collective but not to its individual members. 'Properties of the whole and the information about it pertain to and are determined by the collective rather than its grains' where grains refer to the members. It is noted that properties can be distinct between the collective and the individual grains even if the two are related (e.g., 'the mood of the crowd is distinct from the mood of its constituent individuals').

Collectives are defined as comprising *grains*, or *granular parts* that each 'play the same role within the collective'. A collective does not rely on having a certain number of grains and is not defined by its members. Therefore, they should not be confused with sets. Although the concept of granular parts has been hinted at in research Rector et al. [2006] state that much more needs to be done. Rector et al. [2006] note the apparent neglect of 'the aggregations of individuals into collections' within the biomedical domain. It is noted that collectives are usually considered to be amounts of matter and that collectives can be viewed as amounts of matter when viewed as a single entity at a higher-level. Like DOLCE and SNAP in BFO, entities are represented at a single instant of time.

Collectives can be empty to allow for empty or missing grains: the fact that they are empty is information that may need to be conveyed. Whether or not an empty collective should be considered physical or material has not been addressed by Rector et al. [2006]. The grains within a collective must all be of the same type; it is noted that if a collective has been defined 'in terms of a disjunction' it is more likely that it is a mixture. The majority of collectives are considered to be amounts of matter (i.e., mass entities).

Two types of parthood relation are defined: *granular parthood* and *determinate parthood*. The main distinction between these two parthood relations is the ability to lose parts: the former can lose a grain without the collective being damaged or diminished whereas the latter cannot. Many ontologies within the biomedical domain do not make a distinction between determinate and granular parts; Rector et al. [2006] note that this is likely to be due to the lack of need to do so but also that the situation is likely to change due to the growing need to precisely 'describe individual and collective effects and to distinguish them from effects of physical size'. A distinction is made between granular and determinate parts. Examples given by Rector et al. [2006] of granular and determinate parts are the 'relation of the cells in the finger of the skin to the finger' and 'the relation of the finger to the hand' respectively.

The relations *is-grain of* and *has grain* are non-transitive, irreflexive and asymmetric: no grain can be a 'grain of itself', no collective can be 'a grain of one of its own grains' and 'the grains of grains of a collective are not grains of that collective'. The relation grain-of has been used instead of member-of to avoid confusion with the relation of the same name in mathematical set theory. An argument is put forward for a distinction between *persistent* and *non-persistent parthood*. Persistent parthood occurs when a 'part' can still be referred to once it has separated from the 'whole'; Rector et al. [2006] give an example of a person's finger after it has been amputated, if something fails to develop it can de referred to as being absent. In contrast, non-persistent parts cannot be referred to once separation has taken place (e.g., cells that were once part of an organ).

'Members of a collective often have collective characteristics' (e.g., a pattern or a behaviour) [Rector et al., 2006]. These characteristics cannot be applied to the individual members but to the collective itself. In the same way that a collective's identity does not depend on its extension, the characteristics of a collective do not have to apply to each and every member (i.e., 'are not universal over their extensions'). For these reasons, Rector et al. [2006] represent characteristics as 'properties of the collective'.

Rector et al. [2006] draw attention to the issues that are yet to be resolved: identity of a collective, operations that collectives can undergo and the physical nature of collectives. The issue of identity and being able to track a collective is not considered in bio-ontologies of high-importance since they are usually a-temporal. As Rector et al. [2006] note, this is different from ontologies such as DOLCE and BFO. Since collectives are not defined in extension, the question arises as to what is a collective's identity. No complete answer is given but it is stated that one approach is to take the point of view of an informationalist or a cognitivist: two collectives can be considered the same if 'there is the same information, or continuation of the same, information to be conveyed about them'; but, 'different if there is different information to be conveyed about them'. Operations that a collective can undergo are union and flattening – intersection has not been encountered by the authors.

2.4 Conclusion

Whether or not collectives exist and, if they do, what constitutes a collective are both ontological questions. Within the philosophical literature there is an ongoing debate which discusses whether or not the behaviour of a collective is more than just the aggregated behaviours of its individual members. This argument is acknowledged. However, consider some of the collectives that we may experience in our everyday lives: a flock of birds, a traffic jam, a crowd, or, a queue. With each of these phenomena we attribute properties to the collective as a whole that we do not necessarily associate with their individual members. For example, a queue and a traffic jam can both be thought of as having a length and a crowd a size. A flock of birds may fly in a particular formation. For some collectives, they may be ascribed properties that cannot be assigned to the individual members; it is a jury that decides the final verdict not the individual jurors. This is a point made by Rector et al. [2006] and Bottazzi et al. [2006].

Within natural language we consider a collective as a single entity; we attribute properties to the collective as a whole, not to each and every member of that collective. The reasons as to why we do this are outside the scope of this thesis. However, any framework which aims to facilitate the representation and reasoning about collective phenomena should allow the phenomena to be represented as we think of them (i.e., as individual entities).

The literature that has been reviewed within this Chapter highlights the apparent lack of agreement on whether collectives exist and, if they do, the sort of phenomena that they represent. Although DOLCE does not have any distinct category for collectives, the remaining ontologies all appear to contain at least one category that could represent a form of collective: *aggregate object, collection, group, mob* and *collective*. These categories all refer to a phenomenon that could be considered to have 'collective properties'. However, what these properties are are not commonly agreed.

The minimum number of members required for a collective (or similarly named phenomenon) to exist, varies from zero to two. Rector et al. [2006] state that empty collectives should be allowed since the very fact that they are empty is important information that needs to be conveyed. In contrast Niles and Pease [2001], Bittner et al. [2004], Bottazzi et al. [2006] and Cyccorp [2011], do not allow empty collectives; Bottazzi et al. [2006] states that at least two members are necessary. The identity of a collective is either defined by its members [Masolo et al., 2003; Bittner et al., 2004], a common attribute [Cyccorp, 2011], or unity criterion [Rector et al., 2006; Bottazzi et al., 2006]. This could draw a distinction between two types of collective: those that are defined in extension and those defined in intension; a distinction that may be suitable for a broader range of collectives.

The ontologies SUMO and Cyc, and the work presented by Bottazzi et al. [2006] and Rector et al. [2006] all refer to different types of collective. For example a collective may be homogeneous if its members are all of the same type. Bottazzi et al. [2006] draw attention to some important distinctions between the types of intentional collective by building a typology based on the different types and structures of roles that individual members can adopt and the unity criterion that they can satisfy. Although these refer to only a subset of collectives (i.e., those whose members can be assigned intentionality), they are distinctions that could be applied to a wide range of collectives.

Some of the relationships that are included within the ontologies that have been reviewed could be used to model the relationships that exist between a collective and its member: *constant particpation*, *temporary participation*, *granular parthood*, *determinate* *parthood*, *constitution* and *membership*. However, these relationships are found incapable of modelling the full range of collectives that exist.

This Chapter has highlighted the different notions that exist within the field of applied ontology regarding phenomena that could be referred to as *collectives*. Chapter 3 clarifies the type of phenomena that this thesis will refer to when using the term *collective* and the different types of collective that can be distinguished.

3 A General Taxonomy of Collectives

Although some research has been undertaken into specific types of collectives and collectives within particular domains (Chapter 2), there appears to be no attempt to examine and classify the different types of collectives that exist across the various domains. The collectives from these domains will have some differences, but they also share some common properties which, when used in combination, may allow the different types of collectives to be distinguished. This chapter outlines these properties and the taxonomy of collectives that they form the basis of; a previous edition of the taxonomy was presented by Wood and Galton [2009b].

A prerequisite to developing the taxonomy is defining what is meant by the term *collective*. The review of research within the field of applied ontology (Chapter 2) found no common definition. Instead, different notions of the term *collective* were presented.

Section 3.1 clarifies what the type of phenomenon that is referred to as a collective within this thesis. Following this definition, the criteria that form the basis of the taxonomy are outlined (section 3.2). To illustrate the different types of collective that can be represented using the criteria, a range of examples is given (section 3.3). An analysis of the proposed taxonomy is presented in section 3.4.

3.1 What is a Collective?

Researchers have used many terms to refer to phenomena which comprise more than one individual: *group*, *collection*, *social group*, *aggregates*, *mobs*, *plurailties* and *teams*. This thesis will use the term *collective* as a general term to refer to all of these phenomena. The review of research in Chapter 2 highlighted that no single definition exists of what is meant by the term *collective*. It is clear that a collective must have constituents. This thesis will adopt a similar approach to that proposed by Bittner et al. [2004] and Bottazzi et al. [2006]: a collective can be considered as a single entity that is distinct from any of its individual constituents.

A collective is more than just a group of individuals; there must be a reason for a group of individuals to be considered as a unity but these reasons can vary. A prototypical collective will consist of a group of individuals who have come together to achieve a goal that they cannot achieve individually. However, there are other forms of collective. An external agent may decide that a group of entities should be considered as a collective, albeit a very arbitrary one. For example, all of the items in a bag or all the items in an individual's room. Therefore, it could be said that phenomena exist with degrees of collectivity. For this thesis, a phenomenon will be considered to be a collective if it possess certain properties – what properties a collective has will help to determine the degree of collectivity it exhibits. This section will outline these properties.

3.1.1 Parts and Members

A collective has members. At any given time, there will be a set of individuals which can be considered members of the collective at that time. One of the aims of this thesis is to be able to identify a collective from a spatiotemporal dataset (i.e., the spatiotemporal records of a collective's individual members). Therefore, each individual must be a continuant entity and must be able to be assigned a physical location in space. Each collective must be a *concrete particular*. Abstractions such as mathematical sets will not be considered to be collectives.

Each collective will have a lifespan; it will endure over this period, existing as a whole at each time moment in that period (i.e., a *continuant*). A collective may undergo change during its existence, two possible ways change can occur is in membership or location. Although at any given time there exists a set of individual entities which are considered members of a collective, that collective may not always be identified with the set. As discussed in sections 2.1 and 3.2.1, collectives can be defined in extension or in intension. If defined in extension, then the collective would be defined by its members which could be considered as forming a set. However, the members of an intensionally defined collective will all satisfy a particular criterion; the members may not be the same throughout the collective's lifetime. Indeed, variable membership is an important feature of many collectives, new members can join the collective and existing ones leave. Since the collective need not have the same members at different times, the collective cannot be identified by a set of members. This is in agreement with Rector et al. [2006], who also believe that a collective need not have the same members at two different times. Another distinction between sets of members and collectives is that the former is an abstraction whereas the latter, is concrete.

As noted by Wood and Galton [2009b] collectives can be characterised in terms of their time-varying membership:

$$Collective(x) \rightarrow \forall t \exists S(Set(S) \wedge \forall y(Member(y, x, t) \leftrightarrow y \in S))$$

If we write $members(x, t)$ for the set that is associated with the collective at time t, we have

$$\forall x, y, t(Member(y, x, t) \leftrightarrow y \in members(x, t)).$$

If there is a time t when the collective does not exist, $members(x, t)$ is an empty set. Although Rector et al. [2006] does not use a relationship denoted *membership* to avoid confusion with that of the same name found in set theory, the name seems to best represent the kind of relationship that exists between a collective and its individual members [Galton, 2010]. However, it should be noted that it is different to the set-theoretic relation $\in$.

An important relation exists between a collective and its members. This relation represents one way in which the nature of collectives can be characterised. However, it is important to establish what may be considered as members of a collective. Consider a crowd of people. The members of this collective are the individual people that are participating in the crowd. One could argue that the members are parts of the crowd. However, parthood and membership are not the same relation. If considering the parts of a crowd, the legs, hands and heads of the humans, amongst other bodily parts, would need to be considered in addition to each human body; a point that was made regarding the parthood relation when used for aggregates within BFO (section 2.2.2). Sub-collections could also be possible; for example, the collective of human heads. The differentiation between parthood and membership relations was identified by Winston et al. [1987].

The way in which the members of a collective are identified must also be defined. For example, some individuals may simply be passing through a crowd that is watching a street performer; they do not consider themselves as part of the crowd, but how should the individuals who are members of the crowd be identified without including the individuals who are just passing through?

Bottazzi et al. [2006] and Rector et al. [2006] refer to the members of a collective satisfying some unity criterion and it is this that identifies them as members of a collective. In the example of the crowd, the individuals who are considered members of the collective are those that are present to watch the street performer. In Wood and Galton [2009b], $Collective_F(x)$ was used to denote a collective x whose 'membership-defining property is expressed using the unary predicate F'. Therefore,

$$Collective_F(x) \rightarrow \forall y, t(Member(y, x, t) \leftrightarrow Part(y, x, t) \wedge F(y)).$$

The question can be posed as to what range of properties would be allowed to denote membership. However, as noted by Wood and Galton [2009b] it is difficult to set detailed criteria for this, so this is left as an item to be discussed in Chapter 10.

It is important to note that an individual may be a member of more than one collective at any time; there is no upper-limit to how many collectives an individual may be a member of. For example, at the time of writing this thesis, some of the collectives that I am a member of include: the postgraduate students studying at the University of Exeter, the International Association for Ontology and its Applications (IAOA), the British Computer Society (BCS) and the family 'Wood'.

3.1.2 Granularity

Granularity plays an important role when classifying collectives since the granularity that is chosen is likely to determine what collective is being considered. There are very few phenomena that cannot be considered a collective at some level of granularity. For example, when asked to list the collectives that exist within a typical office it is unlikely that a bookshelf or a table would be selected. However, although at one level both of these items are considered single entities, at a fine level of granularity they themselves could be considered as collectives each comprising the individual pieces of wood that make up the piece of furniture. At a much finer level of granularity, each piece of wood could be thought of as a collective of individual molecules. This is similar to the points made by Grenon and Smith [2004] and Rector et al. [2006] (sections 2.2.2 and 2.3.2).

Second-order collectives do exist (i.e., collectives whose members are collectives). For example, the International Association for Ontology and its Applications (IAOA) can be considered a collective of subscribers. These subscribers could be individuals or institutions where each institution could be thought of as a collective. It is important that such examples of high-level collectives can be identified – it may be a distinguishing feature of these collectives. The concept of second-order collectives could suggest a possible hierarchy of collectives. Indeed, this is a topic that will be discussed by Peter Simons[1]. For the purpose of the research presented here, it simply needs to be noted that a collective of a collective exists.

As already noted, nearly all collectives could be viewed as being second-order at a sufficiently fine granularity. For some applications this may be necessary but for many it is inappropriate. Therefore, it is suggested that the user specify a *base level* before beginning the process of classification. Considered as a granularity constraint, this base level will specify the lowest level that will be considered as admissible members. In some branches of biology a base level of cells or molecules could be appropriate, whereas when considering social phenomena individual humans are likely to be more suitable. For many collectives and applications it would appear that there is a natural base level and below that base level it would not seem appropriate, for that application, to continue.

A user could represent the base level by assigning a suitable *depth* to the application that they are considering [Wood and Galton, 2009b]. The depth refers to the number of levels of members that are to be considered when using the collective under consideration as the reference point. For example, if classifying a herd of animals and considering the individual animals as the base level, the user can specify a depth of one. If, however, the British Computer Society (BCS) is being classified and individual humans should be seen as a base level, a depth of two would be specified since institutions can be members.

3.1.3 Temporality

The way in which a collective is classified is subject to *temporal scope* since the properties that can be ascribed to a collective may differ depending on the period of the collective's existence that is being considered. For example, consider a committee. A committee usually comprises a constant number of people who usually take on a specific role (e.g., chairperson, treasurer or secretary). The size and roles of the committee are properties that can be ascribed to the collective. However, consider the period over which these properties exist. The size of the committee and the roles within it will usually remain

[1] Talk entitled 'Higher-order Collectives' at the workshop "Collectives in Space and Time" in Rostock, 23-25 June.

constant throughout the committee's lifetime but the members who fulfil these roles may change. Now consider the location that can be assigned to the committee. During a meeting, the members will come together to occupy a spatially compact region but between meetings such a location cannot be ascribed. The members will be going about their day-to-day tasks and are likely to be spatially distributed over a large region. Between meetings, the committee is still considered to exist despite exhibiting no spatial coherence or coordinated activities. If a collective is to be accurately classified it should be possible to classify the individual phases that exist within a collective's lifetime because each phase may be classified differently. Therefore, within the taxonomy, a collective's classification may comprise a set of classifications each representing a distinct phase of its existence.

3.1.4 Types and Instances

Collective phenomena can be considered in two ways: as a general type or as a particular instance. For example, general types of collective include: an orchestra, a University and a society; particular instances of these types would be Bournemouth Symphony Orchestra, Exeter University and the British Computer Society. It is important to note that a particular instance need not necessarily be classified in the same way as its type would. For example, consider the committee from the previous section. One may wish to classify a committee (i.e., general type) or a specific instance of a committee such as the Programme Committee of a particular conference (e.g., FOIS 2010). A taxonomy of collectives should be able to classify both types and instances. Although the taxonomy presented here has been developed as one that classifies instances, it is possible to classify general types as seen in section 3.3.

The distinction between classifications of types and instances could be explicitly stated by assigning a T or I subscript to the respective results of the classifications. However, often it is clear when types and instances are being handled since instances usually have a defining name instead of a more general collective noun. Therefore, the use of subscripts to distinguish whether a type or an instance of a collective is being classified has not been adopted within this thesis.

3.2 The Criteria

In the original taxonomy, an analysis of a broad range of collectives led to five classification criteria being identified: membership, coherence, location, roles and depth. They were chosen since, when used in conjunction, they allow distinct classes of collectives to be identified. Since publication [Wood and Galton, 2009b], further research has been undertaken to examine whether these criteria are adequate or need updating. Although no new criteria have been added, some of the existing criteria have been developed. The results of this research will be outlined in the remainder of this section.

As discussed by Wood and Galton [2009b], the application of these criteria may depend on the domain and the views of the user. For example, some may not wish to ascribe intentionality to animals whereas others will. A stand is not taken on these issues within this thesis. Instead, the taxonomy has been developed to be as flexible as possible; users can choose to adopt distinctions that they feel are appropriate and omit those that are not.

3.2.1 Membership

The members of a collective are fundamental to a collective's existence; the membership criterion focuses on the identity and cardinality of these members. The research reviewed in Chapter 2 highlighted some clear views on both of these properties; some stated that a collective is defined by its members or that a collective must have a certain number of members to exist.

Within the taxonomy presented by Wood and Galton [2009b], a distinction was made between those collectives who must always have the same members throughout their lifetime (*constant membership)* and those whose members can change without affecting the identity of the collective (*variable membership*). Of those collectives whose members could change, the cardinality of those members was examined. For example, a string quartet during a performance was classified as having constant membership but, over the entire existence of a string quartet, the members may change – as long as the *number* of members do not change, the string quartet is still considered to be the same (i.e., *constant cardinality*). If one member leaves and is not replaced, or another member is added, the phenomenon that is the 'string quartet' can no longer be considered to exist; at best it is a trio or a quintet. In contrast, many collectives that were classified as having variable membership did not require the same number of members in order to exist (*variable cardinality*). Examples included a crowd, a queue, a traffic jam, a herd of cows and a flock of birds.

Although the inclusion of constant and variable membership within the taxonomy allows two different types of collective to be distinguished, the taxonomy appears to omit an important distinction that has been highlighted within the reviewed research and noted in 2.4: whether a collective has been defined in extension or, in intension. An extensionally defined collective is defined by its members, and therefore, its members cannot change. The members of an intensionally defined collective all satisfy a particular criterion; this could be seen as similar to the concept of a unity criterion given by Rector et al. [2006] and Bottazzi et al. [2006]. For example, contrast 'the string quartet' with 'the founding members of the string quartet'. If the string quartet is not defined by enumerating its members, it has been defined in intension and therefore, can replace members without the identity of the collective being affected. However, the founding members of the quartet will not be able to change - the collective is defined by its members and is therefore, an extensionally defined collective. An intensionally defined collective could relate to a collective that had previously been defined in extension. For example, when founded, the English pop group the *Sugababes*, would have been defined in extension (i.e., as comprising the members Siobhán Donaghy, Mutya Buena and Keisha Buchanan). However, now the pop group referred to as the *Sugababes* do not comprise any of the original members - it is an intensionally defined collective.

Since this is the distinction that is initially trying to be made within the membership criterion, and to align the taxonomy more to the work reviewed in Chapter 2, the taxonomy presented here could make an initial distinction between *extensionally defined collectives* and *intensionally defined collectives.* Examples of the former include the members of the Political Cabinet and the members states of the United Nations, both as of April 2011, and the original cast of the Broadway show Wicked; a string quartet, subscribers to a journal and the inmates of a prison are all examples of intensionally defined collectives. A special form of an intensionally defined collectives could also be considered; those that have switched from being defined in extension to being defined to intension due to continuity (e.g., the *Sugababes*).

However, as Wood and Galton [2009b] note, there are very few collectives that are defined by listing their members; the majority of collectives are described according to the role of the collective or the 'unifying' criterion that the members satisfy. The description of a collective, often what is used to classify a collective, can also be ambiguous due to their *de re* and *de dicto* interpretations [Galton, 2010]. Wood and Galton [2009b] illustrated this ambiguity by comparing two descriptions: 'In five years time all the committee will be dead' and 'In five years time all the committee will be female'. These two descriptions refer to two different collectives denoted as 'the committee': the former is defined by its members (i.e., in extension), indeed the collective may not always be a committee, whereas the second is defined by the role that the collective plays (i.e., in intension). Consider the previous examples of the members of United Nations and the Political Cabinet. If the collectives had been described as comprising the 'current' members instead of the collectives as of April 2011, the ambiguity is clear. Are we describing the particular countries or politicians that make up the collectives at the time of writing this thesis (i.e., a *de re* interpretation); or, are we referring to any country or politician that fulfils role of being in the United Nations or Political Cabinet at the time of reading this thesis (i.e., a *de dicto* interpretation)? As time goes by and the members change, the *de re* interpretation remains fixed but the *de dicto* interpretation will keep track of the changes. The resolution to this ambiguity lies outside the scope of this thesis; however, it could make classification of a collective difficult. Consider one of the illustrative examples used in Wood and Galton [2009b]: an orchestra during a performance. This description could be considered as defining an extensionally defined collective or an intensionally defined collective. Indeed, many collectives could be considered extensionally or intensionally depending on whether the *de re* or *de dicto* interpretation of their description is considered. Therefore, to avoid confusion between whether an intensional or an extensional collective is being considered, the original distinction will be included within the taxonomy presented here (i.e., *constant membership* and *variable membership*).

The cardinality of the members will be included within the membership criterion as a way of further classifying collectives that are considered to be defined as having variable membership. Collectives may require a certain number of members (i.e., *constant cardi-*

nality) or have *variable cardinality*. For example, a jury, must always have twelve members within the United Kingdom. However, a forest need not always have the same number of trees and a children's nursery need not always have the same number of children.

If a collective can be considered as having variable cardinality, a user may wish to include a cardinality constraint within the classification. The taxonomies presented here and by Wood and Galton [2009b] have been developed to be applicable across domains. However, if a user is focussing on a specific domain they may wish to adjust the cardinality constraint to one that is more suited to their application. As analysed in Chapter 2, the minimum number of members required for a phenomenon to be considered a collective has not been agreed. For some, a collective must have a minimum of two members [Bottazzi et al., 2006; Bittner et al., 2004]. This is definitely true of some collectives such as a crowd or a herd. However, some collectives can survive a depletion to one member at some point during its lifetime but continue to exist. The queue at a supermarket may drop to one member for a period of time before increasing in size. Before, during and after the depletion, we still refer to the phenomenon as the 'queue'. Within Wood and Galton [2009b], the possibility of a collective depleting to zero members was discussed. However, it was decided that allowing this would not be considering a collective as a concrete particular; this is carried through to this taxonomy. Up until now only a minimum cardinality constraint has been considered, the question arises as to whether an upper limit may also be necessary. Consider a children's nursery or a particular scout group, each of which can only have so many members due to only a specific number of places being available. However, should this be included as a way of distinguishing between the different types of collective? The minimal number of members has been included since if a collective goes below this cardinality, the collective ceases to exist. This is not true of a collective with an upper-limit – usually collectives can still exist once this limit is reached. Therefore, the taxonomy will continue to only include a minimal cardinality constraint.

It could be questioned if the distinction between constant and variable cardinality is sufficient to classify all collectives. Within Wood and Galton [2009b], the concept of canonical cardinality was briefly discussed. A collective was considered of canonical cardinality if it was meant to have a certain number of members but, if it lost a member, it would continue to exist but be considered damaged or incomplete. Examples given of such collectives included a chess set or the fingers of a hand which should have sixty-four and five members respectively. These types of collective (i.e., those considered as having a canonical number of members), are clearly distinct from those that have already been identified: those that can lose members (i.e., collectives defined in intension) and those that, if a member if lost, cease to exist (i.e., collectives defined in extension). Since these do appear to be three different type of collective, the user should be offered the ability to discriminate between them: those that can gain and lose members whilst retaining their identity, those that are merely considered incomplete or damaged but continue to exist once a member is lost and those that cease to exist upon the loss of a member. However, how should this be represented within the membership criterion?

If the chess set and the fingers of the hand had been defined as having constant membership, the loss of a member would result in the termination of the collective. The chess set could be defined intensionally in the sense that a replacement of its members would not affect the collective's identity. Indeed, it is feasible that a missing finger be replaced via transplant surgery. If defined intensionally, all of the members satisfy a certain 'unity' criterion – if one finger is lost, the remaining fingers still satisfy that criterion and therefore, the collective is still thought to exist. However, the resulting collective is often considered damaged or incomplete. It could be argued that the collective is considered damaged because it cannot function as originally intended. For example, if a chess set loses a piece it can still be thought of as the same chess set but it is considered incomplete because it does not fulfil its function – you cannot play chess with only sixty-three pieces!

It would appear that the distinction that is to be made lies amongst those collectives that can have variable membership but constant cardinality. Categories of this type can be split into *robust* and *weak*. The former refers to those collectives that once a member is lost the collective ceases to exist, the latter to collectives who should not lose members but, if they do, continue to exist but will be considered damaged. The distinction between *robust* and *weak* may not be as clear as one may wish. How many members can a collective which has been classified as *weak constant cardinality* lose before it is considered not just solely incomplete but cease to exist? A user may wish to specify this as a cardinality constraint that defines what is meant by the term *weak*. For example, the fingers of a hand could be classified as having weak constant cardinality. The user may decide that once three out of the four fingers are lost the collective is no longer damaged but ceases to exist. Currently no such constraint has been included within the taxonomy but it could easily be added if the user deems it necessary.

The taxonomy relating to the membership criterion can be found below. Each distinction within the taxonomy is denoted using the format [$\phi\mathbf{x}$] where ϕ refers to the particular criterion (e.g., **M** for the membership criterion), and **x** refers to a particular distinction. **x** takes the form of a sequence of numerals, each successive numeral indicating a refinement of the preceding one.

```
[M1] Constant membership.
[M2] Variable membership.
    [M2.1] Robust constant cardinality.
    [M2.2] Weak constant cardinality.
    [M2.3] Variable cardinality.
        [M2.3.1] Cardinality necessarily > 1.
        [M2.3.2] Cardinality may reduce to 1.
```

3.2.2 Location

When considering a collective from a spatial point of view, two locations can be considered: that of the collective and those of its members. Since the relation between a collective and its members is important in characterising the collective, the relationship between their respective locations should also be examined. A prerequisite of developing this criterion is defining what is meant by the term *location*.

If point-like, an individual's location could be given by a position vector (e.g., longitude and latitude). The location of the collective may be more problematic. The sum of the locations of the individual members could be taken as the location of the collective but the individual members of a collective may be distributed through a very large region of space; the members could be relatively compact but be separated by very large regions of unoccupied space. If the individuals are too widely distributed throughout space it may not be possible to define the collective's location. Consider a committee when not meeting; the members could be distributed across a town or city. If one member goes on holiday, the committee could be distributed across countries. At this time, the committee is still considered to exist but it does not seem sensible to assign the committee a physical location.

When the individual members occupy a relatively small region of space, the sum of the locations of the individual members could form a region referred to as a *footprint* [Galton and Duckham, 2006]. If a collective can be associated with a footprint (i.e., a clearly defined region of space), this thesis will consider it possible to assign it a location. Defining a representative footprint, given a set of locations, is a research field within itself and outside the scope of this thesis. Indeed, Max Dupenois is currently completing a PhD on the topic [Dupenois and Galton, 2009, 2010]; other research within this field includes Duckham et al. [2008] and Galton [2008]. Although not necessarily representative the convex hull could be computed and used as a collective's footprint. For the purpose of this taxonomy it is assumed that a representative footprint has already been determined for a collective; how representative that footprint is is not crucial.

Under this criterion, the collective is initially examined to see whether it can be assigned a useful location. Since there is no distinct rule for establishing whether or not the members of a collective are located close enough in space to be said to be assigned a location, it may be difficult to distinguish between those collectives that can be assigned a location and those that cannot. However, it is a distinction that should be offered to the user.

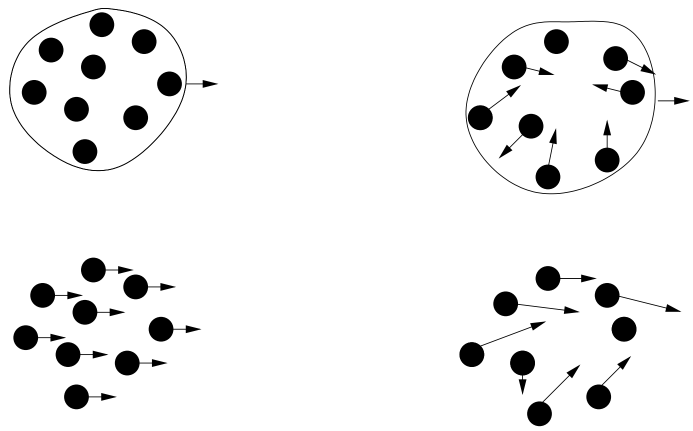
Within Wood and Galton [2009b], a class of schoolchildren was used to illustrate the important role temporal granularity plays in determining whether or not a collective may be assigned a location. Another example is a football team. During training, the football players are likely to occupy a football pitch. When a break occurs, the players may be free to move around the training ground thus occupying a slightly larger region. When training finishes the football players can go to their respective homes. Their houses are likely to be quite widely distributed, possibly over a city or county. Outside of the football season players can go on holiday anywhere that they would like. Holiday destinations could be thousands of miles apart; it does not seem sensible to assign the football team a location when they are this widely distributed. The way in which the football team is classified under this criterion will vary according to the temporal granularity that has been chosen to observe the collective and the phase that it is in (e.g., training or out of season).

If a collective cannot be assigned a location, it could be classified according to whether or not its members can be assigned a location. Physical entities such as humans and animals will always be able to be assigned a physical location. However, if the members are themselves collectives it may not be possible. Examples of collectives which cannot be assigned a location, but whose members can, include a waiting list for a kidney transplant or the participants of a virtual conference. The National Federation of Music Societies cannot be assigned a physical location. Although it has offices around the country, these offices are only for correspondence. Members of the federation are all themselves collectives and therefore cannot necessarily be associated with a location.

Collectives that can be assigned a location could be classified further by looking at whether their location is fixed or variable. Collectives which fall into either of these two categories could be further discriminated according to whether the locations of their members are fixed or variable. For example, a forest is essentially stationary (i.e., has a fixed location) but, a platoon on the march moves through its environment and therefore has a variable location. It may be argued that if the members of a collective have fixed locations the collective must also have a fixed location. However, consider a forest. The trees themselves do not move but, over a period of time, new trees growing and old ones dying may cause the forest's location to appear variable. If one wishes to consider a Mexican Wave as a collective, this collective is a second example; the participants of this phenomenon all remain fixed, it is the collective that moves.

If both the collective and its members were classified as having variable locations in the original taxonomy [Wood and Galton, 2009b], the motion of the collective and those of its members were examined to see if the two motions were coordinated. An approach that would allow this distinction is to take a representative point (e.g., the collective's centroid). The position of this point could be calculated at each time step and its evolution denote the movement pattern that is exhibited by the collective when considered as a single entity. It is true that the motion of a collective will arise from the sum of its individual members' motions (i.e., the vector sum) but this division was included to draw a distinction between collectives whose motion was qualitatively distinct from those of its members (i.e., *uncoordinated*) and those which were qualitatively similar (i.e., *coordinated*). It was noted that this distinction may not necessarily be clear cut and was left to be developed as further research. It has been questioned as to whether the term *coordinated* is the most appropriate. After consideration, it has been decided that the term *correlated* seems to best denote the relationship that is being represented. Two extremes of correlated motion can be seen in figures 3.1a and 3.1b. The top row shows the motions of the individuals in relation to that of the collective and the bottom row the actual motions of the individuals – this is to indicate the relationship between the motion of the collective and the motions of its members. Each vector shown for an individual in the diagram depicted on the bottom row is the vector sum of the two vectors on the top, the individual's vector (zero in the fully co-ordinated case) with the collective's vector.

The individuals' motions could be qualitatively distinct or all of the individuals could exhibit qualitatively similar motion. The qualitative motion of the collectives and the



(a) The movement of the collective and those of its members are correlated.

(b) The motion of the collective and those of its members are not correlated.

Figure 3.1: The two extremes of correlation

individuals are considered as opposed to the quantitative motions since it is the general characteristics of the motion that needs to be captured. When we normally compare two motions, we usually focus on broad categories such as whether the speed of an individual object increases, or whether a motion is linear or circular; it is very unusual for a description to be given quantitatively – often quantitative descriptions would lead to far more distinctions than are necessary. The term similar is used since it is very difficult to calculate whether or not two motions are qualitatively the same. There are many different approaches that a user could take to identify what they consider to be qualitatively similar (e.g., considering individuals that are within a threshold for quantitative measure such as speed and position, comparing distance travelled or distance from starting point, comparing individuals that have the same start and end point); however, the user would have to choose a single approach and use this within the taxonomy. Clearly spatial and temporal granularities will play an important role in determining what is qualitatively similar. Consider a group of dancers that are all moving in a circular pattern. A user may consider the motion of these dancers to be qualitatively similar but what happens if the dancers form three groups: two of which are moving in much smaller circles than the third (e.g., see figure 3.2)? A user may wish to identify two qualitatively distinct motions. This example also illustrates the importance of level of conceptual granularity that has been chosen – the detail in the description of the motion may also determine what is considered to be qualitatively distinct.

If the individuals are all qualitatively distinct, the motions of the individuals and the collective would not be correlated. However, the motion of the collective and the individual members need not be correlated if the individuals exhibit qualitatively similar motion. Consider the dancers around a maypole. All of the dancers could be moving in the same direction around the maypole; however, the collective, when considered as a single entity,

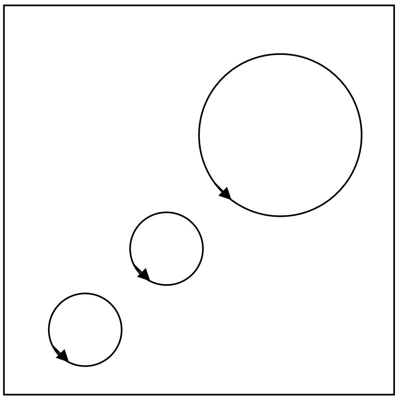


Figure 3.2: An example to show the importance of conceptual granularity - the trajectories of three groups of dancers are shown.

is essentially stationary. The first part of the taxonomy relating to the location criterion can be found below.

```
[L1] Collective cannot be assigned a location.
    [L1.1] Members cannot be assigned a location.
    [L1.2] At least some members can be assigned a location.
[L2] Collective has a location.
    [L2.1] Location of collective is fixed.
        [L2.1.1] Location of members is fixed.
        [L2.1.2] Location of members is variable.
    [L2.2]] Location of collective is variable.
        [L2.2.1] Location of members is fixed.
        [L2.2.2] Location of members is variable.
            [L2.2.2.1] Motion of individuals and collective is
                       correlated.
            [L2.2.2.2] Motion of individuals and collective is not
                       correlated.
```

Since publication, research has been carried out into collective motion [Wood and Galton, 2009a, 2010a,b]. To take into consideration the importance of granularity in the way that both collective and motion are described, collective motion was considered in three ways: the motion exhibited by the collective when considered as a single entity treated as point-like, the evolution of the collective's footprint and the motion of the individuals. Previously referred to as the Three-Level-Analysis (TLA) framework, the movement patterns that were exhibited at each of the three levels were considered independently. Motion was considered as comprising *episodes* where each episode consists of a maximal stretch of motion that is homogeneous at a given level of granularity. The use of episodes can be considered similar to the use of primitives by Dodge et al. [2008]. A more detailed explanation of episodes and the TLA framework can be found in Chapter 8.1. Parts of this framework can be incorporated into the location criterion: the relationship that exists between the motion of the collective and those of its members and, the relationship that exists between the motions of the individual members. The inclusion of this information within the location criterion could be one way in which the motions of the individuals and the collective could be distinguished.

The location criterion could be extended to classify collectives according to the formation of the individual members. The term *formation* is used to refer to whether the relative positions of the individuals are maintained. The individuals could have no formation (i.e., they do not maintain their relative positions), or they could have a *constant* formation. In a constant formation, the individuals are always located in the same position in relation to the other members. For example a platoon on the march will always march in rows. Contrast this with a marching band which do move in formation but this formation could change during a performance; this could be classified as individuals that have a *canonical* formation – there are episodes of constant formation but it may be disrupted outside of these episodes. Another example of *canonical* formation is the passengers on a train. The passengers will all exhibit qualitatively similar motions since they are likely to be sat in a seat. However, it is possible that passengers may wish to move from their seat to purchase food or to change seats and therefore, not maintain their relative positions to the other passengers. Granularity will play an important role in the way in this distinction. For example, the planets all orbit the sun; they could be considered, at a coarse level of granularity as having constant formation. However, at a fine level of granularity the planets that are nearer to the sun can all be seen as orbiting the sun a lot faster than those furthest away from the sun. At this level of granularity, the planets orbiting the sun can be considered as having no formation.

One could comment on the physical movement pattern that is being observed when moving in formation by including the episodes found within the TLA framework (section 8.1), leading to a possible list of formation models. For example, the motion that is being exhibited may be linear or circular, there may be distinct phases within the movement patterns that are repeated. However, for a taxonomy of collectives that does not focus on a specific domain these distinctions appear too detailed and therefore have not been included in this taxonomy. If the taxonomy was to focus on a smaller range of collectives (i.e., a specific domain) this detail may be necessary. The following taxonomy is the second and final part of the taxonomy that relates to the location criterion.

```
[L2.2.2.1] Motion of individuals and collective is
           correlated.
    [L2.2.2.1.1]  No formation.
    [L2.2.2.1.2]  Constant formation.
    [L2.2.2.1.3]  Canonical formation.
[L2.2.2.2] Motion of individuals and collective is
           not correlated.
    [L2.2.2.2.1] The individuals' motions are
                 qualitatively the same.
        [L2.2.2.1.1]  No formation.
        [L2.2.2.1.2]  Constant formation.
        [L2.2.2.1.3]  Canonical formation.
     [L2.2.2.2.2] The individuals' motions are not
                  qualitatively the same.
```

If the motions of the individuals are qualitatively similar then it is likely that they are moving in some form of formation. It has been difficult to enumerate any salient differences amongst collectives whose individuals motions are not qualitatively similar. It is simply noted that the motion of the individuals must be chaotic to some degree and the criterion has yet to be extended in this respect.

It is important to note that, in the development of the location criterion, no assumption has been made regarding the type of space in which the collective is located (e.g., whether the collective exists in a two- or three-dimensional space). Although, the examples that have been given are two-dimensional, the location criterion can be applied to collectives that exist in three-dimensional space.

3.2.3 Coherence

If a phenomenon is to be considered a collective, it must exhibit some coherent behaviour. The source of that behaviour, or collectivity, could allow the different types of collective to be distinguished; this is the focus of this criterion. Historically, the term *coherence* has been used in many different contexts. For the purpose of this thesis, the term *coherence* will be used to refer to the source of the coherent behaviour; this could be seen similar to the notion of a 'unity' criterion given by Rector et al. [2006] and Bottazzi et al. [2006].

In the original taxonomy coherent behaviour could have been spatial or exhibited through the interactions and intercommunications between the individual members. The two main sources of coherence identified were cause and purpose. When coherence can be accredited to 'the action of some cause or collection of causes', which are either internal or external to a collective, that collective is considered causal. Wood and Galton [2009b] give raindrops falling as a causal collective where the coherence is due to an external cause (i.e., gravity); the leaves falling off a tree would be a second example. In these two collectives there is no interaction between the individual members (i.e., the raindrops or the leaves), they are all falling due to the Earth's gravitational pull. Compare this to a star cluster which remains together due to the 'mutual gravitation of its constituent stars'; this is an example of a collective whose coherence is due to an internal cause.

Although some external causes can be inherently causal (e.g. the raindrops or leaves falling due to gravity), external causes can also arise from the physical actions of an external agent. These types of collective are not considered to be purposeful because the source of the coherence is due to the physical actions of the agents occurring irrespective of the purpose behind those actions. For example, a stamp collection owes its coherence to the actions of a collector who has assembled the stamps together in one place (e.g., an album). The movement of the stamps is caused by the actions of the collector even though the actions are purposive in origin.

When a collective is held together by a goal or a purpose, it can be considered purposive. The purpose can be internal to the collective or due to 'the intentions of an external agent'. As discussed by Wood and Galton [2009b], a purposive collective whose purpose is external is distinct from a causal collective whose source of coherence is due to an external agent exerting 'a causal influence on the collective'. The former type of collective exists because of the purpose of the external agent; that agent has not exerted 'any causal influence on it'. Wood and Galton [2009b] described these type of collectives as *purely fiat* and included collectives such as a fantasy football team or a person's top ten list of their favourite musicians. Although these types of collectives are a 'limiting case', and some may not even consider them collectives at all, they have been included to allow a wider variety of collectives to be distinguished.

If the source of a purposive collective is considered internal, the collective can be classified further according to whether 'the collective behaviour arises from a shared collective purpose (i.e., a common intention to achieve some goal collectively)', or ' from the simultaneous exertion of individual purposes (i.e., concurrent intentions to achieve some goal individually)' [Wood and Galton, 2009b]. A public demonstration for a particular cause, or a committee, would be examples of the former and queues and the majority of crowds examples of the latter. The members of a crowd are present due to their individual intentions. For example, in the January sales large crowds of shoppers will gather, each individual wishes to purchase a reduced item. In comparison, each member of a jury will have the goal of contributing their opinion to the final verdict knowing that the other members will have a coordinated goal. Wood and Galton [2009b] highlighted the correspondence between this distinction and the debate of whether 'We-intentionality' can reduce to 'I'intentionality' [Bratman, 1992; Tuomela, 2007; Searle, 1995]. The clear distinction between 'individual purposes' and 'collective purpose' as a collective's source of coherence, means that it is not necessary to comment any further on this controversial issue.

With some collectives it may not be clear whether the source of the coherence is due to cause or purpose, it may even be a mixture of both thus resulting in a criterion that can be subject to gradation. To keep themselves warm during winter, a group of penguins may huddle together. This collective could be seen as purposive since it is the interactions between the members that make us consider them as a collective. However, the collective is also caused by winter – an external cause. Another example is a fire crew attending a fire. The fire fighters all attend to extinguish the fire (i.e., purposive), however, the cause of their coming together is external (i.e., the fire). What follows below is the part of the taxonomy that relates to the coherence criterion.

```
[C1] Coherence due to cause.
    [C1.1] External cause.
        [C1.1.1] Purely causal.
        [C1.1.2] Cause arising from external purpose.
    [C1.2] Internal cause.
[C2] Coherence due to purpose.
    [C2.1] External purpose (purely fiat).
    [C2.2] Internal purpose.
        [C2.2.1] Individual purposes.
        [C2.2.2] Collective purpose.
```

3.2.4 Differentiation of Roles

In order for a phenomenon to be referred to as a collective within Rector et al. [2006], all of the individual members, which are referred to as 'grains', must play the same role. Although this is suitable for the biological examples that Rector et al. [2006] are considering, it is not suitable for a wider spectrum of collectives where the members may or may not play different roles within the collective. For example, the trees within a forest cannot be distinguished by role but the members of a committee could. Whether or not the individuals can be differentiated by role and, if so, how they may be differentiated is the focus of this criterion.

If the members of a collective can be differentiated by role, the collective can be said to follow a certain type of *role structure*. The structure that the individuals adopt may be a distinct feature of that type of collective. There are numerous different role structures that exist, far too many to enumerate in this thesis. The original taxonomy distinguished between four: hierarchical, oligarchic, partitioned and individualistic, but combined the former two resulting in three ways in which collectives could be classified under the role criterion. The list was not intended to be exhaustive and the gradations that exist between these models were acknowledged.

In its simplest form, a hierarchical model consists of an oligarchic structure where an individual or small group of individuals take a leadership role and the remaining members do not play any role at all, they simply 'follow'. More complex hierarchies will have more than one level within the hierarchy and are often found in businesses and institutions. An individualistic model is the opposite to a hierarchy, each individual plays its own distinct role within the collective. Examples include a barbershop choir or a Political Cabinet. Between these two structures lies what have been labelled *partitioned models*. Within these collectives there exist a small number of roles each of which is taken on by a subset of the members of the collective (i.e., sub-collectives). Since the sub-collectives are themselves collectives, they could also be classified under this criterion. An orchestra comprises four sections: strings, woodwind, brass and percussion, and could therefore be considered to follow a partitioned model. The string section consists of the violin, viola, cello and double-bass sections each of which will have a leader and therefore follow a hierarchical model. The brass and woodwind sections are individualistic since the musicians within these sections will each play their own parts.

Research undertaken since developing the original taxonomy has not led to the inclusion of any further models. However, the structure of this criterion has been updated. Although omitted from the original taxonomy it was noted that a distinction could be made between collectives where the roles that each member plays is constant throughout the lifetime of the collective and those where members may change roles. For example, in a family the roles of mother and father remain; however, new committee members may be re-elected and current members retire. This could be an important difference between collectives and therefore, for each model, a collective can be classified as following a *constant role structure* or a *variable role structure*. This provides a distinction between collectives where the same individual plays the same role throughout the existence of the collective and those where the individual that plays a certain role may change without the identity of the collective being affected. If this distinction is considered inappropriate for the user, it can be omitted.

Two possible representations of the section of the taxonomy relating to role can be found below. This criterion can be presented in two ways since what is really being represented is a cross-classification but in the form of a hierarchy. Ideally, the cross-classification would not be be present; however, it has been included here for continuity.

```
[R1] Members of collective are not differentiated by role.
[R2] Members are at least partly differentiated by role.
    [R2.1] Hierarchical.
        [R2.1.1] Constant role structure.
        [R2.1.2] Variable role structure.
    [R2.2] Partitioned.
        [R2.2.1] Constant role structure.
        [R2.2.2] Variable role structure.
    [R2.3] Individualistic.
        [R2.3.1] Constant role structure.
        [R2.3.2] Variable role structure.
```

or

```
[R1] Members of collective are not differentiated by role.
[R2] Members are at least partly differentiated by role.
    [R2.1] Constant role structure.
        [R2.1.1]  Hierarchical.
        [R2.1.2] Partitioned.
        [R2.1.3] Individualistic.
    [R2.2] Variable role structure.
        [R2.2.1]  Hierarchical.
        [R2.2.2] Partitioned.
        [R2.2.3] Individualistic.
```

3.2.5 Depth

As outlined in section 4.5 a collective may consist of members that may be individuals or collectives. Collectives of collectives were referred to as *second-order collectives*. Base levels and depths were used to specify the number of levels of members that a user wishes to consider. This criterion distinguishes between collectives whose members are collectives and collectives whose members are base level individuals. This approach allows collectives of any depth to be considered.

An initial distinction can be made between those collectives which contain collectives as members and those that do not. A collective may not consist solely of individuals or collectives, but a mixture of both. Examples of such collectives have already been discussed in this chapter (i.e., the BCS and IAOA). A distinction can be made between those collectives which have no collectives as members and those that have some members which are collectives. The latter can be split further into collectives which only comprise members that are collectives and collectives which do not consist solely of collectives. It could be considered confusing as to what the specified depth would be in collectives whose members are collectives and individuals. As suggested by Wood and Galton [2009b] the collective could be represented as a tree-like structure and the depth taken as the length of the longest branch.

It is important to note the difference between a collective of collectives and a partitioned collective. A collective can be classified as following a partitioned role structure if sub-collectives within the collective can be distinguished by the roles that they play. Each member of one of these sub-collectives is still considered to be a member of the overall collective. For example, the members of the strings, woodwind, brass and percussion sections are all considered members of the orchestra. In contrast, the Russell Group comprises twenty universities as its members. Each university can be considered as a collective comprising its staff and students but these staff and students are not members of the Russell Group. This is the key distinction between partitioned collectives and collectives of collectives: members of a member of a collective are not members of the collective itself (i.e., membership is not transitive).

Presented below is the final part of the taxonomy, which relates to the depth criterion.

```
[D1] No members are collectives.
[D2] Some members are collectives.
    [D2.1] Not all members are collectives.
    [D2.2] All members are collectives.
```

The classification under this criterion has been organised according to the number of members that are collectives; it could also be organised in terms of how many members are base-level individuals.

3.3 Illustrative Examples

The taxonomy can distinguish amongst a wide variety of collectives with examples including: the trees in an orchard, a constellation (on the scale of a human life-time), the moons of Jupiter, a jury during a court session, the wheels of a car, the atoms of a water molecule, the alumni of a university, the European Union, the National Federation of Music Societies, a protest march (with or without leaders), leaves blowing around the garden, cars parked in a carpark, an audience at a lecture, the inmates of a prison and the passengers in a train. Wood and Galton [2009b] illustrate how these collectives would have been classified under the existing taxonomy. However, due to the additional criteria, some of these examples can be updated; examples of these updates can be found in table 3.1. To aid the interpretation of the table, a copy of the full taxonomy follows; for the criterion relating to role, the first possible representation has been used.

Membership:

```
[M1] Constant membership.
[M2] Variable membership.
    [M2.1] Robust constant cardinality.
    [M2.2] Weak constant cardinality.
    [M2.3] Variable cardinality.
        [M2.3.1] Cardinality necessarily > 1.
        [M2.3.2] Cardinality may reduce to 1.
```

Location:

```
[L1] Collective cannot be assigned a location.
    [L1.1] Members cannot be assigned a location.
    [L1.2] At least some members can be assigned a location.
[L2] Collective has a location.
    [L2.1] Location of collective is fixed.
        [L2.1.1] Location of members is fixed.
        [L2.1.2] Location of members is variable.
    [L2.2]] Location of collective is variable.
```

```
      [L2.2.1] Location of members is fixed.
      [L2.2.2] Location of members is variable.
          [L2.2.2.1] Motion of individuals and collective is
                     correlated.
              [L2.2.2.1.1]  No formation.
              [L2.2.2.1.2]  Constant formation.
              [L2.2.2.1.3]  Canonical formation.
          [L2.2.2.2] Motion of individuals and collective is not
                     correlated.
              [L2.2.2.2.1] The individuals' motions are
                           qualitatively the same.
                  [L2.2.2.1.1]  No formation.
                  [L2.2.2.1.2]  Constant formation.
                  [L2.2.2.1.3]  Canonical formation.
               [L2.2.2.2.2] The individuals' motions are not
                            qualitatively the same.
```

Coherence:

```
[C1] Coherence due to cause.
    [C1.1] External cause.
        [C1.1.1] Purely causal.
        [C1.1.2] Cause arising from external purpose.
    [C1.2] Internal cause.
[C2] Coherence due to purpose.
    [C2.1] External purpose (purely fiat).
    [C2.2] Internal purpose.
        [C2.2.1] Individual purposes.
        [C2.2.2] Collective purpose.
```

Differentiation of Role:

```
[R1] Members of collective are not differentiated by role.
[R2] Members are at least partly differentiated by role.
    [R2.1] Hierarchical.
        [R2.1.1] Constant role structure.
        [R2.1.2] Variable role structure.
    [R2.2] Partitioned.
        [R2.2.1] Constant role structure.
        [R2.2.2] Variable role structure.
    [R2.3] Individualistic.
        [R2.3.1] Constant role structure.
        [R2.3.2] Variable role structure.
```

Depth:

```
[D1] No members are collectives.
[D2] Some members are collectives.
    [D2.1] Not all members are collectives.
    [D2.2] All members are collectives.
```

Classification					Description	Examples
M1	L2.1.2	C2.2.2	R2.2.1	D1	A collective consisting of a constant set of individuals which follow a partitioned, constant role structure and whose coherence is due to an internal collective purpose. The location of the collective is fixed but the locations of its members are variable.	A football team during a match
M1	L2.2.2.1.1	C1.1.1	R1	D1	A collective consisting of a constant set of individuals which are not differentiated by role and whose coherence is due to an external non-purposive cause. The motion of the collective and its members are correlated with the individuals moving without formation.	The moons of Jupiter
M2.1	L1.2	C2.2.2	R2.3.2	D1	A collective with variable membership and robust constant cardinality. Members are individuals which follow an individualistic, variable role model and whose coherence is due to an internal collective purpose. The collective cannot be assigned a location but its members can.	A string quartet over a period
M2.3.1	L1.2	C2.2.2	R2.1.2	D1	A collective with variable membership but cardinality >1. Members are individuals which follow a hierarchical, variable role structure and whose coherence is due to an internal collective purpose. The collective cannot be assigned a location but its members can.	A University Debating society
M2.3.2	L2.1.2	C1.1.2	R2.2.1	D1	A collective with variable membership but cardinality >1. Members are individuals which follow a partitioned, constant role structure and whose coherence is due to an external cause arising from an external purpose. The location of the collective is fixed but the locations of its members are variable.	Chess pieces in play during a game

Classification					Description	Examples
M2.3.1	L2.2.2.1.2	C1.2	R2.2.1	D1	A collective with variable membership but cardinality >1. Members are individuals which follow a partitioned, constant role structure and whose coherence is due to an internal cause. The motion of the collective and its members are correlated with the individuals moving in canonical formation.	The cells making up an individual human heart
M2.3.1	L2.2.2.1	C2.2.2	R1	D1	A collective with variable membership but cardinality >1. Members are individuals which are not differentiated by role and whose coherence is due to an internal collective purpose. The motion of the collective and its members are correlated with individual members moving in a canonical formation.	A protest march (without leaders)
M2.3.1	L2.2.2.1.3	C2.2.2	R2.1.1	D1	A collective with variable membership but cardinality >1. Members are individuals which follow a hierarchical, constant role model and whose coherence is due to an internal collective purpose. The motion of the collective and its members are not correlated but the individual participants' motions are qualitatively similar but without formation.	Participants of a battle
M2.3.2	L1.2	C1.1.2	R1	D1	A collective with variable membership whose cardinality may reduce to 1. Members are individuals which are not differentiated by role and whose coherence is due to an external cause arising from an external purpose. The collective cannot be assigned a location but its members can.	Books currently on loan from a library

Table 3.1: Illustrative examples of the general taxonomy of collectives.

3.4 Discussion

The classification that has been proposed would appear to allow a wide variety of collectives to be distinguished according to the various criteria; if the five criteria were mutually exclusive, 7560 ($5 \times 12 \times 6 \times 7 \times 3$) different types of collective could be classified. However, it is clear that dependencies exist between some of the criteria. Some questions regarding fundamental aspects of collectives are also yet to be addressed.

3.4.1 Dependencies

The five criteria that form the basis of the taxonomy are not mutually exclusive and some dependencies do exist. If one distinction within a criterion necessitates or rules out a distinction in a second criterion, a dependency is said to exist between those two criteria. There are cases where the position of a particular collective within one criterion reflects its position in a second such as collectives whose members' roles are determined by their spatial location (e.g., ships identified as rescue ships due to their proximity to the ship that needs assistance). However, these examples are not dependencies; a dependency requires that no collective can have a particular combination of distinctions or all collectives that are classified using a particular distinction in one criterion must be classified using a certain distinction under a second criterion (e.g., collectives whose members can be assigned locations must themselves also be collectives). Since there are cases where a role does not depend on spatial location (e.g., the roles of a committee), no dependency exists between the role and location criteria.

Ideally the dependencies between the criteria would have been identified empirically with examples given for each type of collective (i.e., each possible combination) that exists within the taxonomy. However, although many examples have been identified, it has proven difficult to find examples for each and every combination. Therefore, the dependencies have been identified theoretically. Each of the distinctions made within a criterion were systematically compared to all distinctions made in each of the other four criteria.

Two dependencies had been previously discussed within Wood and Galton [2009b]. The first stated that if the members of a collective could not be assigned locations, then they themselves must also be collectives (i.e., a collective of type L1.1 must be of type D2.2). It was noted by Wood and Galton [2009b] that collectives which were made up of members that were both individuals and collectives (D2.1) are unlikely to be considered as not being differentiated by role (R1) since if some of the members are individuals and some are collectives, that in itself would seem to constitute a differentiation of roles. However, a definitive statement can still not be made on this.

The results from systematically searching for dependencies has failed to reveal many more than those identified by Wood and Galton [2009b]. One possible dependancy identified within the search is that any collective considered as having constant membership (M1) must be a purely fiat collective (C2.1). If a collective is defined as having constant membership, the collective is defined by its members (i.e., in extension). If the collective was exhibiting general coherence, the members of a collective would be satisfying some unity criteria (i.e., the property deemed as producing the general coherence) and therefore, be intensionally defined. A purely fiat collective is only a collective since an external agent deems it to be (i.e., it is defined by its members). Due to this reasoning, it is suggested that collectives of type M1 must be of type C2.1. The term, *suggested* is used since this dependency has not been empirically proven.

If the three suggested dependencies are considered, 2010 possible combinations can be ruled out resulting in 5550 possible collectives that the taxonomy can distinguish between.

3.4.2 Possible Problems

The taxonomy is believed to be able to classify 5550 different collectives. However, there are questions that still need to be addressed.

Section 3.3 has highlighted that not all examples are easy to classify. The five criteria that form the basis of the taxonomy are not always easily applied to a description, especially if that description is ambiguous or referring to a general type of collective. Consider the collective which is described as the 'participants of a battle'. Within 3.3, the participants are classified as not moving in formation – this may not be true of all battle environments. The participants may adopt a canonical formation. Therefore, the user should always ensure that the most appropriate description is given for each collective before it is classified.

Although a more detailed description may clear up some ambiguity, it is possible that ambiguities will still occur. Section 3.2.1 highlighted that there is often more than one way of viewing a given collective due to the way that its description is interpreted (e.g., if both a *de re* and *de dicto* interpretation of the description can be considered) – the user should be aware of any ambiguities that may occur and try to deal with them accordingly (e.g., try to find a more appropriate description and ensure understanding of the description).

As already noted, the taxonomy presented here is able to classify both types and instances of collectives. However, when classifying types, the finest-grained subcategories in the presented taxonomy may not be applicable; different instances of the type may be classified into different such subcategories. In this case, the type could be classified according to what is possible. For example, if one wishes to classify the collective type flock of animals, an allowance must be given for both naturally-forming flocks of type C1.2 and flocks assembled by human agency of type C1.1.2. The classification in this case could be given as a disjunction, say C1.1.2 $\vee$ C1.2, or by naming the most specific superordinate category, in this case C1.

Some of the distinctions that are made within the criteria are not always clear. For example, deciding whether or not a collective can be associated with a location, or distinguishing between weak and robust constant cardinality. Possible ways that the distinctions can be made have been suggested but no definitive rules are given. In some cases, gradations are possible (e.g., between the different role structure models). The taxonomy has been designed to applicable across domains and it is difficult to see how rules could be provided for these distinctions which could apply to multliple domains.

3.5 Conclusion

This chapter has clarified what is meant by the term *collective*. Although no detailed definition can be given, the properties of a true collective have been enumerated. Collectives are concrete particulars and continuants. The members of a collective may change during the lifetime of the collective but at any given time they must have at least one member. Since variable membership is possible, a collective cannot always be identified by a set of members. Therefore, collectives are considered to be characterised in terms of their time-varying membership with the relation $members(s, t)$ denoted the set of members s that is associated with that collective at time t. The properties that a collective has, determines the degree of collectivity that it exhibits.

A taxonomy has been presented that is formed by identifying the common properties that are shared by collectives as a class: membership, coherence, location, depth and differentiation of roles. It is difficult to fully evaluate the taxonomy since no existing examples can be found for comparison. Instead the taxonomy has been evaluated through examples and theoretical research. A wide range of different collectives have been enumerated and classified using the taxonomy. The way in which collectives are classified is dependent on granularity and temporality; it is important that both of these aspects are taken into consideration when developing a framework that aims to classify a collective. The location criterion classifies a collective based on its location within space; distinctions are made according to whether or not positions can be assigned to the collective and its members. Since these distinctions can be made regardless of the space that a collective exists in, the taxonomy can be applied to collectives that exist in both two- and three-dimensional space.

A systematic search for dependencies between the distinctions made within the five criteria has led to only three being identified; the lack of empirical examples resulted in the search being carried out theoretically. However, examples are continuously being gathered to try to allow for an empirical analysis.

The illustrative examples that have been provided within section 3.3 have highlighted that it is not always easy to apply the criteria to a description especially if that description is ambiguous. It is suggested that someone trying to use the taxonomy should always ensure they fully understand the collective that they are trying to classify and that they have not misinterpreted the description.

It should be noted that aspects of the original taxonomy [Wood and Galton, 2009b] have been used by Ong et al. [2010]. Within Ong et al. [2010] a ‘pattern interpretation framework’ is proposed which aims to ‘support the understanding of movement patterns’ extracted with a ‘trajectory mining algorithm’. The framework comprises three steps: pattern discovery, semantic annotation and pattern analysis. The criteria proposed in the original taxonomy [Wood and Galton, 2009b] are used as a ‘guideline for selecting the thematic attributes used in the semantic annotation process’. Interestingly, these criteria are used to interpret ‘collective types of patterns’. The proposed approach has been applied to a dataset that records the movement of visitors in Dwingelderveld National Park.

The ultimate goal of the research presented here is to identify the existence of a collective within a spatiotemporal dataset; it may be possible that a taxonomy, such as that presented here, could be applied to groups of individuals within the dataset to identify the presence of a collective. However, the taxonomy is capable of distinguishing between a wide variety of collective phenomena; it may not be possible to identify all of the necessary information from a movement dataset. Therefore, Chapter 4 analyses existing research within the field of movement pattern analysis to see what has already been accomplished.

4 Movement Pattern Analysis Involving Collectives

The movement patterns that are exhibited by collective phenomena are one of the most important features that one may wish to reason about. Consider a protest march or a football match. Both of these events involve examples of collectives whose movement patterns are crucial. Police must know the movements of the group of protesters, especially if they change course; and, a football match would not be the same if one or neither of the teams moved!

An increase in the availability of technologies capable of tracking individuals and objects has led to an increase in the amount of movement pattern data. A dataset could record multiple trips made by one individual or the movement of multiple entities. Usually this *raw data* will contain many spatiotemporal records for each individual [Mountain and Raper, 2001a,b; Dykes and Mountain, 2003], where each record is an $\langle i, \overrightarrow{x}, t \rangle$ triple which records the position vector $\overrightarrow{x}$ of individual i at time t. The number of records for each individual will depend on the observation period that is being considered and the sampling rate used.

Movement pattern analysis can help identify more meaningful information about the individuals and objects whose movement patterns have been recorded including whether a collective is present within the data. For example, consider a traffic management system. Officials could use the movement patterns exhibited by the traffic to identify the occurrence of a traffic jam by detecting a cluster of stationary vehicles. The research presented within this thesis aims to identify the presence of a collective within a movement dataset. The taxonomy presented in Chapter 3 has identified many different types of collective but it is unclear whether all of these collectives could be identified within such a dataset and, also, whether all of the necessary information for classification would be available. Therefore, this Chapter examines research within movement pattern analysis that focuses on the motion exhibited by collectives (i.e., *collective motion*).

Some may argue that the movement patterns that one is looking for must be identified and defined before they can be extracted from a dataset and analysed. Therefore the task of movement analysis, could be considered as comprising two components: definition and extraction. This Chapter will examine the relevant research according to these two components. Although focussing on those that analyse the movement patterns exhibited by collectives, research which deals only with the movement of an individual will still be considered where a concept is discussed or proposed that is important to movement pattern analysis in general.

4.1 What is Movement?

A pre-requisite to developing a definition of any movement pattern is to define exactly what is meant by the term *movement*. To extract information about the behaviour of an individual from a dataset that contains that individual's spatiotemporal record, an analyst must understand the data that has been collected and how it has been recorded. Andrienko and Andrienko [2007b] define movement as a function which matches pairs *(entity, time moment)* with positions in space. From these pairs *derivative movement characteristics* can be derived such as direction, speed and their changes (called *turn* and *acceleration* respectively). Although much of the existing research agrees with this representation of movement, the way in which movement is conceptualised can vary.

Dodge et al. [2008] note the need to fully understand movement and its properties and develop a conceptual framework which focuses on the elements that movement comprises. Referred to as the *primitives of movement*, these elements include both the parameters of movement and the external factors that may influence movement. Three groups of movement parameters are given where the first, *primitive parameters*, is used to derive the second two: *primary derivatives* and *secondary derivatives*. Within each of the three groups the parameters are organised according to whether they occur in the spatial, temporal or spatiotemporal dimension. For example, an object's *position* is given as the sole spatial primitive. From this, the *distance*, *direction* and *spatial extent* are considered primitive derivatives; secondary derivatives are given as the *spatial distribution*, *change of direction* and *sinuosity*.

Similar to the use of primitives is the use of *episodes* [Mountain and Raper, 2001a,b; Dykes and Mountain, 2003]: periods of activity which are 'relatively homogeneous' [Mountain and Raper, 2001a]. *HyperGeo* was a EU funded project which aimed to develop a 'prototype tourist information system' which would deliver up-to-date 'user-sensitive information' as well as the user's location. The project involved a group of institutions each working on a component of the overall system. Mountain and Raper [2001a] presents the work undertaken by City University London which included the development of a suitable tracking device (the Position Tracker) and a piece of software, the Location Trends Extractor (LTE), which would analyse the data to discover trends and provide a summary of the data thus allowing a user's spatiotemporal behaviour to be modelled. The LTE presents the data to an analyst who can visualise the types of information that may be extracted. From this, a set of episodes are defined (e.g., a countryside walk and 'a single car journey'). For each user, a user profile is constructed which records their spatiotemporal data (i.e., their position at each time step); it is this profile that is then analysed to establish a user's spatiotemporal behaviour.

Indices such as absolute speed, sinuosity and direction can be calculated from the raw data at different temporal scales. Using the LTE, an analyst can focus on a section of the data where a particular speed, distance or sinuosity has been calculated. A sudden change in any of these indices, spatial coordinates or temporal dimension, highlights a breakpoint and, therefore, the beginning of a new episode. For example, GPS devices cannot transmit a location when inside a building, therefore, if a break is found in longitude recordings, a new episode could be defined. Additional knowledge can be obtained if 'exogeneous' information is added to the episodes. Such information could include constraints in the environment, potential destinations and network information (e.g., speed constraints).

Two types of interval are defined by Dykes and Mountain [2003]: a 'space-time' and a 'time-space'. The former is where a temporal range is defined by a spatial limit ('when a user is in a particular space'); the second is where a spatial range is defined by a temporal limit ('where a user is during a particular period'). Breakpoints allow limits to be applied to space-times and time-spaces, both of which are derived from the data. Since segmentation is data-driven, Dykes and Mountain [2003] note that this method is less arbitrary than looking at 'particular scales' or periods.

Episodes are a useful way of conceptualising movement data, as a set of homogeneous activities, and could allow patterns to be detected within the data [Wood and Galton, 2009a]. For example, the different traffic flows that occur in succession at a road when the traffic light changes between red, amber and green. However, it must be possible to automatically analyse the data when conceptualised in this way. Mountain and Raper [2001a] suggest the use of *enveloping*. An envelope can be defined as 'the minimum enclosing rectangle for a set of points'. It is a method used to minimise the search space. Within Mountain and Raper [2001a], three types of envelope are identified to analyse a point set: spatial, temporal and map-display according to whether spatial, temporal or map coordinates are used to define the boundary of the rectangle.

Spaccapietra et al. [2008] and Yan [2009] consider an analysis of the evolution of the position of a moving object to be incomplete unless the relevant 'semantic' information has been included. The evolution of the position of a moving object is considered as comprising a set of trajectories: 'semantic' objects that can be represented using a time-space function. Since travelling suggests that the movement has a purpose, a movement pattern must be considered as a 'countable journey' for it to be a trajectory. Defined by the user, this function will record how the position of an object, considered as a point, evolves over time to achieve its own specific goal. Each trajectory is restricted to a particular distinct time interval, a segment of the overall lifespan of the moving object; the time interval will begin when the object starts to travel and will only end when the goal has been satisfied. The way in which the path of the object is split into trajectories will depend on the application and the semantics it associates with a trajectory but could also be determined by the observation period [Spaccapietra et al., 2008; Yan, 2009]. An example given by Spaccapietra et al. [2008], is the flight of a migrating bird; some experts may consider the flight as two trajectories, outbound and return, others may consider this as only one.

A detailed explanation is given on what is meant by the 'semantics of trajectories'. For each application, what is 'relevant to the conceptual view' will depend on that application's requirements. However, some generic characteristics are outlined. Each trajectory is considered to contain up to four different types of component: *begin*, *end*, *stops* and *moves*. Each trajectory will be defined by a specific time interval and delimited by a begin and an end. Within this interval, the object will be classified as either moving (i.e., a move) or not (a stop); no point within a trajectory will not belong to either of these two components. It is important to note that a stop is not necessarily a physical stop; it must have been defined by the application as a legitimate stop. Spaccapietra et al. [2008] give an example of a salesperson who can have two types of stop: a refreshment break or a meeting with a customer. The application may determine that only the latter be counted as a stop. Begins and ends are not considered stops.

The semantics should assign meaning to each of the four components or to add application dependent constraints. For example, the beginning and end of a trajectory must be the company's premises; or, if trajectories are confined to a network (e.g., traffic), constraints would be needed to ensure that the trajectories conform to that network. Other examples of constraints given are that a plane cannot fly without a pilot and crew, and white storks do not fly at night. Similar to Andrienko and Andrienko [2007b], movement characteristics such as speed and direction are computed from the raw data.

4.2 Defining Movement Patterns

In many cases, it is important to know what you are trying to locate before beginning the search. Much of the existing research defines possible movement patterns, many of which are relevant to collectives. When considering collective motion, some existing research has focused on particular examples of collective phenomena (e.g., herds), while others have formed taxonomies of movement patterns some of which relate to the class of collectives in general. Much of this research appears to focus on the levels of the individuals, considering the motion to arise from the decisions that are made by the individuals or the rules that they follow.

4.2.1 Focussing on the Levels of the Individuals

Different interactions that occur between individuals can result in a variety of group motions. Many researchers have noted the importance of internal factors on group movement pattern; one such factor could be the interactions that occur between individuals.

Animal groups such as flocks and herd can exhibit very complex motion. However, to simulate this in computer animations can be very difficult and time consuming, especially if the paths of individual animals must be 'scripted'. Reynolds [1987] believe that flocking arises from the interactions between the individual behaviours of the birds and have developed an approach to simulate flocking accordingly.

The method that is proposed by Reynolds [1987] uses a 'distributed behavioural model'. Referred to as *boids*, each individual within the system is considered similarly to that of a particle in a particle system. However, in contrast to particles, boids are represented as a geometric object. As well as aiding the visual appearance of the system, this representation also allows each boid to have an orientation – a boid has 'a full local coordinate system and a reference to a geometrical shape model'. Within a particle system, particles do not necessarily interact. This cannot be true of boids; the birds that they simulate must interact in order to exhibit flocking. Therefore, a boid's behaviour is dependent on both their internal state and an external state. Within Reynolds [1987] a detailed description is given of the system that has been developed. However, what is of interest to this thesis, is the behaviours of the boids that allow the flocking to take place.

Reynolds [1987] state that if birds are to participate in flocks, it must be possible for each bird to coordinate their behaviour with other birds within the flock. To simulate the flock, each boid follows three rules: 'collision avoidance', 'velocity matching' and 'flock centering'; these rules have come to be known respectively as *separation*, *alignment* and *cohesion*. Collision avoidance allows birds to avoid each other within the flock; velocity matching means that each boid will try to match its velocity (a vector comprising speed and direction) with that of nearby boids. Flock centering results in boids trying to stay close to other boids within the flock. Each boid has a localised perception of the world, thus the centre of a flock is simply the centre of any group of boids that are nearby. Initial positions, velocities and orientation are always randomised at the beginning of each simulation. However, the rules that govern the behaviour of the boids allow them to participate in a motion that is similar to flocking. Boids stay near to each other but at a suitable distance. Due to velocity matching, they also quickly begin to move in similar directions and at similar speeds; this also results in synchronous changes in direction.

Eftimie et al. [2007] focus on three similar interactions as the rules followed by the boids: *attraction*, *repulsion* and *alignment*. Considering communication as a medium for these interactions, four different signals are given: *acoustic*, *chemical*, *visual* and *tactile*. In the definition of these signals both their range and directionality are considered. Eftimie et al. [2007] build a 'non-local continuum model' from these definitions to help explain how animal groups form and move 'in response to the information that they receive'. From the definitions of these interactions, and the ways in which they can be combined, Eftimie et al. [2007] indicate the various spatial patterns that are formed. The movement patterns that are defined include: *stationary pulses*, *travelling pulses*, *travelling trains* and *zigzag pulses*. Stationary pulses and travelling pulses are both spatially inhomogeneous but the former is a steady state and the latter two have a fixed shape and occurs when speed is constant. Travelling trains and zigzag pulses are both 'periodic' but zigzag pulses are ones that can change direction.

Currently, simulation results have shown that only the essential features of complex biological patterns can be compared. Eftimie et al. [2007] note that their model, which is one-dimensional, would need to be extended to two dimensions if more general and realistic cases of communications could be handled. Topaz and Bertozzi [2004] have developed a two-dimensional continuum model which is also designed to explore 'pattern-forming behaviour' resulting from interactions between organisms; the ultimate goal of their research is to be able to 'make specific statements about how social interactions between organisms affect the large-scale motion of a biological group' [25]. A particular type of collective motion is focused on swarming; another movement pattern that is similar to those found in a group of boids [Reynolds, 1987].

The model that Topaz and Bertozzi [2004] have built is based upon four assumptions. One such assumption is that the population is always conserved; immigration, emigration, birth and death are considered negligible. As discussed in Chapter 3, variable membership is as an important feature of many collectives, and one that could impact on their movement patterns.

Although the effects of external factors are noted as important by Eftimie et al. [2007], neither they nor Topaz and Bertozzi [2004] consider them in their models. Such factors may come from an entity's environment and are likely to affect the motion of that entity. Batty et al. [2003] consider how an individual's environment may affect that individual's movement and have developed a model to simulate the effects of a route change on the Notting Hill Carnival. Barriers, police and mobile attractions (i.e., floats) are all viewed as 'mobile agents' within a geometric landscape, an approach that enables a wider range of interactions to be considered because 'the behaviour that 'emerges' from the accumulated interactions between small scale objects' can be modelled. Issues such as planning and management can arise when large numbers of people are interacting and moving. Batty et al. [2003] wish to introduce models that are based on the dynamics of local movement and can be generalised to many different 'small-scale spatial events'. These models will allow the related spatial problems to be reasoned about and solved.

When focusing on the level of the individuals, an alternative approach to analysing the effect of interactions between the individuals, is to analyse how the decisions of individuals affect the overall behaviour of the group that they are participating in. Some research that looks at the movement patterns exhibited by collectives focus on those that are self-organising [Gueron et al., 1996; Sumpter, 2006].

Gueron et al. [1996] use a set of hierarchical decisions that individuals make within a herd as the basis of a mathematical model. Although only described as a 'starting point', the model allows the analysis of the affect of the defined decisions on the movement patterns, shapes and cohesion of the self-organising group. Gueron et al. [1996] view patterns forming due to the actions of the individuals in relation to their neighbours or 'local environmental signals or markers' (i.e., the co-ordination of the group is locally controlled). They note that the shape of the group will be affected by changes in environmental conditions, but that other external factors need not be considered.

Instead of focussing on particular collectives, Sumpter [2006] analyses a wide range of self-organizing collectives whose members are animals. This analysis has lead Sumpter [2006] to note that the movement patterns exhibited by these types of collective 'can be explained using rules which the individual members follow'. The aim of the research is the development of a set of principles which could be used to develop 'behavioural algorithms that individuals could follow'; such algorithms could form the basis of mathematical models that can predict the collective behaviour of animal aggregations. To develop these algorithms Sumpter [2006] generates an initial list of principles within which the common features of the observed collective animal behaviour are included: individual integrity, inhibition, redundancy, leadership and synchronisation Sumpter [2006] notes that these principles are not intended to be thought of in isolation; further studies are required to see how they may interact to form 'complex collective patterns'.

Huang et al. [2008] note that the ability to detect and describe spatiotemporal patterns are crucial if a greater understanding is to be obtained of the behaviour of moving objects, and list some of the many applications where one must understand the behaviour of moving objects: surveillance, transport analysis and defence. The focus of the work presented within Huang et al. [2008], is to find groups of moving entities from trajectory data – a goal that is very similar to the research presented here. A new conceptual definition is presented for the spatiotemporal pattern *herd* along with four types of *herd involvements*: expand, shrink, join and leave.

The pattern 'herd' is related to flocks. It is noted that the notion of a flock, and the flock finding algorithms reviewed by Huang et al. [2008], are all based on a set of parameters that must be defined by the user: the minimum number of entities, duration of time interval and a radius – this radius states the area that all the entities must be located in. Some limitations with flock-based approaches given by Huang et al. [2008] include the possibility of flocks overlapping and the algorithms only identifying a subset of the entities that are flocking; the possible lack of consideration that flocks are not necessarily circular in shape; and, also not fully considering that flocks move and evolve over time. Given these limitations, Huang et al. [2008] focus on the travelling patterns of groups and the ways in which these groups can evolve and interact.

Assuming uniform sampling, each timestep is referred to as a *snapshot*. A density-clustering based method is used to identify groups that are spatially proximate; a group of entities identified at a timestep is referred to as a *herd snapshot*. Herd snapshots can be related to each other by representing the movement and 'evolvements' of a herd over time.

Herd evolvements occur when members of a herd change. An examination of how membership changes can lead to various formation of herds and how these changes can characterise herd evolvements, has led to the definition of four herd evolvements: expand, join, leave and shrink. Expand occurs when 'many' of the existing herd are joined by 'substantial' new members; join when a new herd joins an existing herd but there is still a majority of members from the original herd. A herd is considered to shrink if a 'substantial' number of members is not present within the herd at that time step compared to the herd at the previous time step. A herd (H_1) can leave an existing herd (H) if the members of H_1 were also members of herd H at a previous time step. Once the members of H_1 have left H, the remaining members form the herd H_2(t); this resulting herd must be "similar" to the previous herd H [Huang et al., 2008].

A distinction is made between qualitative and quantitative changes. The former occurs when so many members change that there is not a good representation of the herd anymore. The latter occurs when change in membership is reasonably small resulting in a reasonably good representation of the original herd. It is noted that these changes will depend on the definitions used for good and reasonable. Through mathematical measurements, herd evolvements can be extracted from the dataset.

Huang et al. [2008] illustrate that each herd evolvement can be measured using measurements such as Precision, Recall and F_{Score} - all measurements traditionally used to evaluate the performance of Information Retrieval systems. Considering moving entities as documents, these measurements are used to produce conceptual definitions of each of the four evolvements.

A discussion is given regarding the identity problem, and therefore labelling, of two herds after they have undergone a process of splitting or merging. To overcome this problem a ranking system is proposed. At the start of clustering, the set of entities that have been identified as a herd at that time will be defined as the core members. A herd will continue to be represented by this core member set until the actual members of the herd deviates qualitatively from the core member set; qualitative difference is represented by the F_{score}. At this point, the original herd will disappear and a new herd emerges with a new core member set.

4.2.2 Taxonomies

Two relevant taxonomies have been developed: one that focuses on entities that are found in the urban planning domain [Thériault et al., 1999]; and, one that examines movement patterns in general [Dodge et al., 2008]. Although the former is not intended to be exhaustive (i.e., focuses on a particular domain) and the latter includes patterns that are not specific to collective phenomena, both taxonomies address and discuss important concepts that will need to be considered when developing a system capable of processing collective motion.

Thériault et al. [1999] propose a taxonomy that classifies sets of geographical entities (SGEs) which are located in a geographical space and share a thematic or functional relationship. The proposed framework is based on a set of assumptions. As noted in section 5.2.3, where a more detailed discussion can be found on these assumptions, many of them appear sensible but some could be questioned. For example, the needs of the application are used to decide what measurement units will be chosen for space and time – it is stated that they do not intend to 'identify propagation rules across geographical scales and temporal granularities'. As discussed within section 8.1, the way in which motion is described is often dependent on the level of granularity at which it is observed [Wood and Galton, 2009a].

Two sets have been identified to produce the taxonomy: one to define the spatiotemporal properties which characterise the geographical evolution of the set of entities and one to define the 'basic evolution processes of the geographical entities'. The properties of the geographical entities (GE) are computed attributes which are found using statistical aggregation methods, and are represented at both the entity and the set level. By representing the properties at the two levels, the taxonomy can represent groups of entities which may exhibit simple behaviour even though the behaviour of the set may be complex, thus making it difficult to define the the 'homogeneous spatial properties for sets'.

Each entity is assigned an intensity value which denotes how important it is in the study. The way in which an entity can evolve over space and time is restricted to changes that involve points; an entity is considered to have no shape, size or orientation. This would not be suitable for the representation of collectives. Consider two collectives: one whose members are closely packed together and one where the spaces between the individual members is quite large. In the former the size of each entity is likely to affect the dynamics of the collective and in the latter the entities could be considered as points since the size of the individuals are unlikely to affect the collective motion.

Spatial and spatiotemporal profiles are used to allow measurements and comparisons of the patterns formed from the way in which GEs are distributed through space. Spatial profiles measure the location of entities at or over a given time period while spatiotemporal profiles measure both location and time. These two profiles can be combined with movement measures such as travelling speed to allow the spatiotemporal behaviours of either entities or sets of entities to be compared. Spatiotemporal profiles could be considered similar to the user-profiles used within Mountain and Raper [2001a].

Thériault et al. [1999] distinguishes between four 'basic components of spatial evolution' that are all relevant to the transportation modelling domain: the spatial distribution of entities within the domain, an SGE's footprint, the geographical arrangement of the entities and the presence of spatial autocorrelation. Existing statistical methods can be used to measure these four components and examples are given for each. Although only considered for the transportation domain, these components would also be relevant to a much broader range of collectives. They do not intend to build a formal taxonomy of these processes or show how the properties of entities are transferred or aggregated to the sets which they form; this is left to future research. The spatiotemporal processes that involve relevant sets of GEs are identified. Thériault et al. [1999] focus on how changes of a GE affect the evolution of the SGE that it is a member of and in particular the changes that relate to the life of each GE, the movement of entities and the movement of the entire SGE.

Possible changes in the life of each GE include its leaving or joining an SGE. Set membership of a SGE can result in changes in the size and density of its footprint, which they choose to represent as a minimum convex polygon. GEs could move around while remaining within the boundary of the SGE's footprint; however the movement of a GE could lead to its interaction with the boundary. If entities move outside the current footprint of the SGE but remain a member then the footprint will expand. However, if entities all move inwards (away from the SGEs boundary) then the SGE's footprint will contract. As discussed by Wood and Galton [2008], variable membership is an important feature of many collectives and, as highlighted by Thériault et al. [1999], this feature will affect the way in which collective motion is interpreted. When discussing the possible changes in the movement of the entire SGE, only the co-ordinated movements of GEs are considered; they do not consider partial co-ordination. Of the possible co-ordinated movements they only consider the possibilities of GEs moving at the same speed and direction and GEs moving at different speeds but 'turning around a central point'.

A review of existing literature into the discovery of movement patterns in domains such as data mining and visual analytics has shown that there is little agreement on the variation of movement patterns that exist and very few movement patterns have been defined. This has led Dodge et al. [2008] to begin to develop a taxonomy of movement patterns. Although not completed, the taxonomy that is presented highlights the problems of defining movement patterns and introduces a range of concepts and definitions that could prove useful in the development of a classification of collective motion. However, since the focus is not on movement patterns that are specific to collectives there are still a number of questions left unanswered and problems unsolved.

The need to fully understand movement and its properties are noted and a conceptual framework is developed which focuses on the elements that movement comprises (i.e., the *primitives of movement*). A discussion of these primitives can be found in section 4.1. The conceptual framework, defines four groups of influencing factors: 'the intrinsic properties of the moving object', the spatial constraints, the environment where the movement is taking place, and other agents. Dodge et al. [2008] have designed their influencing factors to be as generic as possible since they vary according to the type of entity. It is noted that this contrasts with the approach of Andrienko and Andrienko [2007a] who have developed a classification of influencing factors; however, Dodge et al. [2008] believe that with 'respect to the behavioural characteristics of movement', their classes are defined better by using their approach. It is difficult to see if this is indeed true. Further research would be required to see the impact of this design choice on classifying or identifying collectives within a dataset or if there may be a more efficient method.

Dodge et al. [2008] do note that the behaviour of moving objects will differ according to whether they are travelling alone or in a group. A distinction is made between groups where members 'share a behaviourally relevant functional relationship' and cohorts whose members, while lacking such a relationship, exhibit a common factor that is of some statistical relevance. This distinction is one of importance but it is lost in their proposed taxonomy which only distinguishes between individuals and groups; they consider the type of relationship that exists between the individuals in a collection only useful in the interpretation of movement patterns and not in their definition.

The taxonomy proposed by Dodge et al. [2008] is based on the relevant literature that they have reviewed to ensure that redundant terminology is minimised. This has resulted in many of the movement patterns defined by Andrienko and Andrienko [2007b] and Laube et al. [2005] being included. For example, the movement pattern *co-location* is included from Andrienko and Andrienko [2007b]; two examples of this movement pattern can be found in figure 4.1, which shows *ordered* and *unordered* co-location; this figure has been taken from Dodge et al. [2008]. Dodge et al. [2008] have included some new movement patterns and an organisation scheme to produce the taxonomy.

Primarily the proposed taxonomy is organised according to the two pattern types distinguished by Dodge et al. [2008]: *generic patterns* and *behavioural patterns*. The former are movement patterns that can be found in 'any form of behaviour' but the latter covers movement that is specific to particular types of moving object. Generic patterns can be thought of as the building blocks for forming behavioural patterns. Since generic patterns can also range in complexity they are further categorised into primitive patterns, where

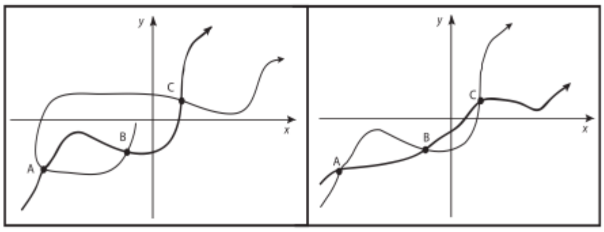


Figure 4.1: Two examples of co-location in space: unordered (left) and ordered (right) [Dodge et al., 2008].

only one movement parameter varies, and compound patterns which comprise a set of primitive patterns. After distinguishing by type, the taxonomy is then organised into the dimensions that possible movement patterns can occur in. Primitive patterns are split into three: spatial, temporal and spatiotemporal; compound patterns are only categorised as spatiotemporal and behavioural patterns are not further categorised. After the second distinction, a list of movement patterns are given some of which are split into sub-categories. If focussing on collective motion, some of these patterns could be organised further by considering the structure of the motion (section 8.1).

The importance of granularity in analysing a movement pattern is noted by Dodge et al. [2008] but they believe that the decision of what temporal and spatial granularity to use is specific to a domain and it is therefore somewhat ignored by their classification.

4.2.3 Other

Andrienko and Andrienko [2007b] wish to develop a tool-set that would allow an analyst to detect movement patterns of multiple entities in vast movement data. However, to do this the patterns that an analyst may wish to detect must be determined and therefore the properties and the structure of movement data considered. Although no taxonomy is proposed, a detailed list is given of the movement characteristics and patterns that are specific to multiple entities; importantly it is the collective movement of such entities that Andrienko and Andrienko [2007b] wish to focus their analysis on.

A definition of a pattern is given; it is noted that various patterns can be built out of the basic elements: 'pattern types' and 'pattern properties'. A specific pattern is treated as an 'instantiation of one or more pattern types'. An analyst will look for constructs in the data that can be related to known pattern types; once found, the pattern properties of the found constructs will be observed and measured. As Andrienko and Andrienko [2007b] note, this means that the pattern types that are relevant to the data that is being analysed need to be defined.

When dealing with multiple entities, Andrienko and Andrienko [2007b] distinguish between categories of what an analyst may wish to observe the movement characteristics of: a single entity over time, a set of entities at a given single time moment and multiple entities over a certain period (i.e., taking a holistic view). These are designated *Individ-*

ual Movement Behaviour (IMB), *Momentary Collective Behaviour (MCB)* and *Dynamic Collective Behaviour (DCB)* respectively. The characteristics of an IMB are given as the path and distance travelled, the movement vector and the variation of speed and direction. The 'synoptic characteristics' of a MCB is given as 'the distribution of the entities in space, the spatial variation of the derivative movement characteristics, and the statistical distribution of the derivative characteristics over the set of entities'.

It is the DCB that is believed to be the focus of interest when analysing the movements of multiple entities [Andrienko and Andrienko, 2007b]. Various factors are listed that could influence the behaviours and movement characteristics of an entity; these are divided into four main categories: properties of space (e.g., a terrain's characteristics), properties of time (e.g., temporal cycle), properties and activities of the moving entities (e.g., means and way of movement), and various spatial, temporal and spatiotemporal phenomena such as weather, customs and legal regulations. Andrienko and Andrienko [2007b] summarise the goal of an analyst, who focuses on the movement of multiple entities, to relate the DCB to these four factors as well as describing and comparing the dynamic collective behaviour.

A DCB can be described from two points of view: as 'the behaviour of the IMB over the set of entities' and as 'the behaviour of the MCB over time'; these two views are referred to as 'aspectual behaviours' [Andrienko and Andrienko, 2007b]. These two aspectual behaviours are considered as being fundamentally different and therefore needing to be described using different pattern types. Andrienko and Andrienko [2006] had previously defined what are deemed to be the four most general types of pattern, three of which are seen as relevant when detecting patterns using visual analysis alone: *similarity*, *difference* and *arrangement*. Arrangement patterns can only be considered when observing MCB since they examine the 'changes in the MCB with respect to the ordering and distances between the corresponding time moments' [Andrienko and Andrienko, 2007b]. Four different specialisations of a similarity pattern are listed: *similarity of overall characteristics* (e.g., travelled distances), *co-location in space*, *synchronisation in time* and *co-incidence in space and time*. Co-location in space occurs if the paths followed by the observed entities contains the same, or at least some, of the same positions; this similarity pattern can be further distinguished according to whether the shared positions are visited in the same order ('ordered co-location'), in different orders ('order-irrelevant co-location') or in opposite orders ('symmetry').

The pattern types which describe DCB behaviour are a combination of the three basic pattern types and include: *constancy*, *change*, *trend*, *fluctuation*, *pattern change or pattern difference*, *repetition*, *periodicity* and *symmetry*. All these patterns are referred to as *descriptive* because they allow us to describe a DCB. In order to describe the relation 'between the DCB and properties of space, time, entities, external phenomena, and events' it is stated that additional types of pattern must be used. Referred to as *connectional patterns* these include *correlation*, *influence* and *structure*. Structure allows complex behaviour to be considered that is built from simpler ones. Influence occurs when phenomena produce effects on others. Correlation can look at co-occurrence of any characteristics.

In common with many other researchers, Laube et al. [2005], note that new ways are needed to analyse and interpret moving object data; their research tries to increase the 'analytical power' of GIScience when exploring the motion of objects. Laube et al. [2005] presents the 'RElative MOtion (REMO) analysis concept' which allows motion attributes of point objects to be compared over space and time and also an object's motion to be related to that of others in the dataset. In addition, REMO allows the user to predefine the motion patterns that need to be detected using a formalism, also presented in Laube et al. [2005]. Moving point objects are modelled using 'geospatial lifelines'; these consist of three pieces of data: *id*, *location* and *time*. This could be considered similar to the those used within Hornsby and Egenhofer [2002].

A two-dimensional matrix is used (the *REMO matrix*) whose rows represent objects and columns represent time-steps. The first step in the REMO analysis concept involves the population of the matrix with the motion attributes *speed*, *change* and *motion azimuth*. A pattern in REMO is defined as 'a set of motion parameter values' which extend in time and across the objects. Primitive patterns are those that are only present in one dimension of the matrix and include *constancy*, *concurrence* and *change*; however, these can be used to build 'complex patterns'. For example, constancy and concurrence can be combined to form a complex pattern which they name 'trend-setter'.

By considering the 'interrelations' that occur in both dimensions of the matrix, any complex interactions that occur between multiple moving objects can be considered. To detect the motion patterns that have been predefined, the REMO analysis concept uses 'syntactic pattern recognition'; in this technique the pattern is seen as comprising 'simpler subpatterns' (i.e., primitives). A description of possible pattern matching algorithms is given along with a reasonably detailed discussion of how the REMO analysis concept compares to other tools which analyse spatiotemporal data (e.g., database management systems, data mining, descriptive statistics and exploratory spatial data analysis (ESDA)). One way in which Laube et al. [2005] state that their approach improves on these existing tools is the ability of the REMO analysis concept to analyse the movement data of multiple individuals concurrently. Figure 4.2 is used by Laube et al. [2005] to illustrate the basic REMO concept: the geospatial lifelines (a) are transformed into the REMO matrix (b) and (c), which is then used to identify REMO patterns (d). In figure 4.2, the patterns identified are constancy, concurrence and trend-setter.

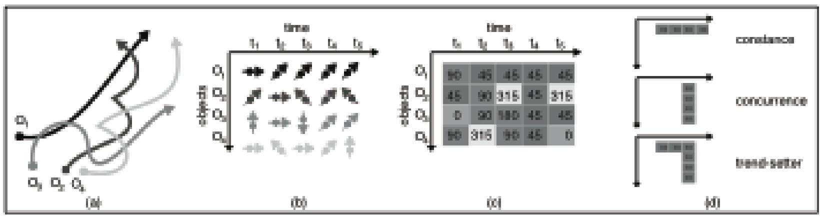


Figure 4.2: The REMO concept
[Laube et al., 2005].

It is pointed out within Raper and Livingstone [1995] that movement in itself is continuous but in order for it to be recorded and analysed in information systems, the 'essential characteristics' must be represented in a discrete form. This affects the problem of granularity, especially the problem of choosing the most appropriate level of granularity. If too coarse a temporal granularity is chosen undersampling will occur and important information is lost; however, too fine a granularity may lead to oversampling and possibly high levels of noise with 'feigned autocorrelation' being introduced between consecutive moves [Laube et al., 2005]. It is suggested that undersampling can be avoided if data are collected at the 'highest granularity possible'; oversampling can be lessened by resampling the tracks of the moving objects at increasingly coarse levels of granularity until 'autocorrelation between the moves disappears'. The importance of being able to change the temporal granularity is noted (i.e., *temporal zooming* [Hornsby, 2001], see section 4.5); if all the available information from the data is to be uncovered it is vital that a system can move between 'more and less detailed views'.

The REMO analysis concept has been tested on a diverse range of data: within Laube et al. [2005], the model is evaluated by applying it to football players on a pitch and 'data points in an abstract ideological space'. These two very different examples highlight the broad range of applications that the REMO analysis concept could be applied to and the wider range of motion patterns that can be defined and extracted for database datasets. However, as noted by Benkert et al. [2006] and Andersson et al. [2008], REMO only requires a pattern to exist at one time step for it to be recognised as a pattern such as flocking. Benkert et al. [2006] argues that this may not be suitable for all practical applications (e.g., where a group of animals must stay together for an extended period of time before they are considered to be a flock).

Many of the approaches that have been considered so far in this Chapter, focus on the location-based aspect of movement, or extracting similar movement parameters. Hornsby and Cole [2007] distinguishes the different kinds of movement by examining the events that a moving object experiences.

Hornsby and Cole [2007] note the importance of considering the relative movements of objects when considering groups of moving objects. Although research has led to some basic patterns of group motion to be defined [Laube et al., 2005], Hornsby and Cole [2007] state that these existing classifications could be extended if movement patterns could be characterised according to the sequences of events experienced by a moving object.

When moving through a domain, an object will experience different occurrents (section 2.1) it is from the view of these occurrents that the movement of an entity is described. Occurrents are modelled as events, each having an identifier of the object which it is associated with, a name, a reference to the region of space or *zone* that the event occurs and a timestamp of when the event occurred. Events are modelled as instantaneous – they simply mark a change in state of an object.

The collection of occurrents that a continuant will experience as it moves through the domain are referred to as an *event sequence*: a set of temporally ordered events. A *transit* is an event sequence that represents the occurrents an entity experiences as it moves through the domain – in its simplest form, it could be a sequence of change zone events. A specialised event occurs when an event satisfies a set of conditions (e.g., DepartEvent occurs when previous zone is the departure zone).

Patterns can occur in event sequences or transit; identifying these patterns could help in the monitoring and managing of events and the movements that are associated with them. An example of a traffic jam is given – a pattern that would require other traffic to be redirected if the jam is to be alleviated. Candidate events are events that can be aggregated to form event combinations; these combinations can then be used to reveal patterns of events.

Hornsby and Cole [2007] illustrate 2^3 different patterns of possible events depending on whether values are the same for events in a combination (e.g., two events could have the same identifier since they are associated with the same objects, if they are associated with different objects, the identifiers will not be the same). Four of the patterns that are listed can only occur in when event combinations come from the same transit, the remaining four can only occur if the transits of multiple entities are considered. Notable patterns are considered for each of the eight combinations. With regards to patterns involving multiple entities, a *reiterating pattern* is considered notable. The pattern occurs when multiple objects are associated with instances of the same event class that occur in the same zone and within a constraining time window. Hornsby and Cole [2007] give an example of a group of motorists who all change lanes and therefore, possibly indicating that an accident has occurred.

4.3 Extraction

Movement pattern analysis aims to extract information from movement data that has been captured via suitable tracking technologies. If a set of movement patterns has been previously identified, this information can usually be found via computation. However, what happens if an analyst does not have a list of pre-defined movement patterns? How can information regarding an individual's behaviour be extracted from a dataset of spatiotemporal records? This section examines two relevant extraction methods that have been suggested in the existing research: clustering and similarity calculations.

Clustering allows groups of objects to be identified whose members share a common property or attribute; such a group may be a collective. It can be used as a tool to indicate the distribution of the data, identify areas that could be analysed further or for preprocessing (e.g., produce clusters that can be used by other algorithms) [Huang et al., 2008]. Traditional clustering methods use feature vectors to represent the entity that is to be clustered. However, as Andrienko et al. [2009] note, 'trajectories or moving entities' are complex objects that cannot be adequately represented using traditional methods. An analyst must also consider the computational expense of dealing with movement datasets which are often very large and complex. Often a dataset cannot be loaded into memory in its entirety; performing computations on a dataset when it is held out of memory can be very time-consuming.

Andrienko and Andrienko have continuously recognised the importance of a human when analysing and interpreting movement data [Andrienko and Andrienko, 2006, 2007a; Andrienko et al., 2009]. Different parameters can be used in clustering each of which could provide more meaningful results for a human analyst. Therefore, Andrienko et al. [2009] propose a method that 'allows interactive cluster analysis of large numbers of structurally complex objects'.

The proposed method comprises two stages and requires the selection of a manageable and representative subset of the dataset that is to be clustered. In the first stage, a generic density-based clustering algorithm is applied to this subset to produce a *classifier*. The classifier is then applied to the rest of the dataset and the remaining objects attached to the datasets found in the first stage. A classifier comprises prototypes for each cluster, the appropriate distance threshold and a distance function – this threshold has been used for the clustering. In each of the clusters found in the first stage, one or more prototypes objects (prototype) are selected – these objects are all located within a distance below the distance threshold to the other objects in the same cluster.

A human analyst will analyse the classifier to ensure the data have been appropriately classified. They may choose to refine the classifier using prior knowledge of properties of the dataset, to ensure new objects are assigned correctly to existing clusters or, if they believe misclassification has taken place. Once the analyst is satisfied with the classifier, it is applied to the whole dataset. An object is compared to an existing cluster by comparison with the prototypes. If the distance of a new object is below the predefined threshold to a prototype, the object is attached to that cluster. If it is not close enough to any cluster it remains unclassified. If there is a choice of more than one cluster, the closest is chosen.

The approach that has been proposed by Andrienko et al. [2009] requires the dataset to be stored in a database and a distance function to be defined. It is also stated that the results of the clustering should be graphically summarised and objects visually represented according to the distance function. The computation time for classification will depend on the number of objects in the dataset but as Andrienko et al. [2009] note, their proposed approach is scalable for larger datasets.

An alternative approach to clustering is analysing the similarities between trajectories. Similarity between trajectories is a reasonably new research topic. Dodge et al. [2009] wish to analyse the characteristics of the movement behaviour of different types of moving entities and extract any possible occurring similarities. A method is proposed which extracts the movement parameters from the trajectories of different moving objects. This method could be used to develop 'rigorous algorithm evaluation strategies', find similarities between real and simulated data, or classify the trajectories of unknown moving objects according to the trajectory types of moving object; within Dodge et al. [2009] the focus is on the second two applications.

An increasing number of research projects are focussing on the analysis of the trajectories of moving objects [Dodge et al., 2009]. Although many methods have been proposed to analyse such data, the majority are theoretical; very few have been 'implemented and applied in practice'. Dodge et al. [2009] note that a reason for this could be the difficulty in finding suitable datasets to which new methods could be applied. Often researchers have to contend with privacy, security and cost issues. To overcome this difficulty Dodge et al. [2009] state that simulated or other available data could be used as a proxy. For example, the dispersals of bank notes could be used as a proxy for human movement behaviour.

Dodge et al. [2009] define a moving object as an object which changes position or whose 'geometric attributes change over time'. Objects are considered as points and, therefore, the dimensions of the object are ignored. They distinguish between two types of moving object according to whether they move in geographic or non-geographic space. They note that much of the existing research focuses on the former type of moving point object (MPO). Examples of the first include humans, vehicles and animals; eye-movement data would be an example of the latter. Although there are similarities between the two, they also exhibit important differences in their nature, structure and behaviour.

The focus of the analysis by Dodge et al. [2009] is on trajectories (i.e., the paths of moving objects). The parameters of a moving object's trajectory had already been identified in Dodge et al. [2008] including speed, acceleration, duration, sinuosity, path, displacement and direction. These parameters can be considered as the 'building blocks' of movement; Each type of MPO will usually exhibit, to 'some degree', 'different signatures' of these primitives, or descriptors as they are referred to in Dodge et al. [2009]. Dodge et al. [2009] argue that these descriptors can be used to extract examples from a dataset or replicate behaviour of objects of a similar type. each can be defined in an absolute sense and a relative sense. Interestingly Dodge et al. [2009] state that a relative sense can include a comparison to previous states of the same MPO in addition to the relation to other MPOs.

The method proposed by Dodge et al. [2009] comprises three stages: prepare trajectory data, compute global descriptors and extract local features. The raw data is likely to contain 'noise, outliers and gaps' due to the sensitivities of GPS [Hoffmann-Wellenhof et al., 2001]. Therefore, within the first stage of the proposed method, the data is cleaned and pre-processed. Pre-processing involves the removal of outliers using filtering, re-sampling to obtain trajectories at regular intervals and smoothing to eliminate noise. The descriptors can all be computed from the raw data in stage two. Within the method, the descriptors are computed for each point along the trajectory. It is suggested that the descriptors are initially calculated by looking at the entire trajectory along with global statistics, the results of which can be analysed using correlation analysis. To extract local features, plots are compiled of how a movement parameter evolves over time to produce a profile or a function. Different types of MPOs are likely to have different profiles thus allowing extraction of local features. Each profile is decomposed into 'segments of homogeneous movement characteristics' according to sinuosity or the deviation from median line; this could be similar to the episode approach (section 4.1).

Although a list of possible applications for the proposed method is given, the paper focuses on the classification of trajectories within transportation and eye-tracking data. The movement characteristics of known types of MPO have previously been extracted and learnt; unknown MO trajectory data is classified based on this knowledge. Using a supervised classification method, the method is applied to the data to see if the mode of transportation can be automatically detected from the data and if eye-tracking data could be used as a proxy for different types of MPOs. Through three experiments, eye-movement trajectories are found to be much less smooth than those of cars, pedestrians, motorbikes and bicycles. However, it is noted that this is dependent on the level of granularity at which the data is analysed.

4.4 Visualisation

The visual analysis of the data in movement pattern analysis is an important tool; however, with large datasets, visual analysis can be very difficult and, on its own, insufficient. Many visualisation techniques have been suggested in the research. However, only one will be discussed in this thesis, aggregation. Aggregation is of direct relevance to this thesis since it deals with the visualisation of multiple data points, some of which could be collectives. Other visualisation techniques such as interactive cubes [Kapler and Wright, 2005] and animated maps [Andrienko et al., 2000] are more suited to the visualisation of an individual's movement and therefore, are not discussed here since they are not suitable for visualising the movement of a group of individuals.

Previous research that has been undertaken within Andrienko and Andrienko [2008] has proposed a 'formal model of collective movement of multiple entities'. A function is defined $\mu : E \times T \rightarrow S$, which describes the set of all possible positions (S) given a set of moving entities (E) and the continuous set of time moments (T). Since μ is defined as a function of two independent variables, it can be viewed in two ways: a *trajectory-oriented view* or a *traffic-oriented view*. The former describes the 'set of all trajectories of all entities'; the latter 'a temporal sequence of traffic situations'. The term *traffic situation* describes 'the spatial positions of all entities at a time moment t'.

It is noted that the term *traffic* refers to the collective movement of all entities. Through examples, Andrienko and Andrienko [2008] show that the analysis that is needed will determine which view to adopt. Each of the two views needs a different type of aggregation. It is noted that most software tools that facilitate the visualisation of large datasets use some form of aggregation. Three different 'basic types of aggregation' exist: temporal, spatial and attributive. A T- aggregation is presented as a temporal histogram with each bar representing a time-step and its height proportional to what is being counted (e.g., number of locations visited). A S-aggregation imposes a regular grid over the region that is being examined and counts the trajectory points that are found within each grid cell; colour and shading can be used to display densities. These basic types can be used in different combinations. A $S \times T$- aggregation computes densities for consecutive time intervals, the results of which can be visualised using an animated map display. Andrienko and Andrienko [2008] note that these aggregation methods consider only independent events and therefore, do not capture the specific nature of movement data.

A trajectory-orientated view considers the collective movement of a group of entities. One approach is to group trajectories based on their similarity [Meratnia and de By, 2002; Kuijpers and Moelans, 2008; Pelekis et al., 2009]. Another approach is to aggregate by origin and destination; further analysis could then examine those entities that have common origins and destinations. Aggregations could also be made according to route or the locations visited by entities in between their origin and destination.

For movement data, an $S \times T \times D-$ aggregation is suggested where D refers to the direction of travel. If not present within the data, this additional information can be computed. To aid analysis, direction could be split into suitable intervals such as north, east, south and west. Where speed is below a certain threshold, an entity is not considered to be moving.

4.5 Granularity

The description of motion is very much dependent on the level of granularity at which it is observed. Some of the literature that has been reviewed in this Chapter, involves the decomposition of complex movement patterns into simpler ones [Mountain and Raper, 2001b; Dykes and Mountain, 2003; Laube et al., 2005; Andrienko and Andrienko, 2007b; Dodge et al., 2008]. The approach of using primitives as 'building blocks' to form more complex movement patterns could be considered an approach that allowed motion to be considered over more than one level of granularity. However, such primitives must be chosen with care. Consider walking as an example. At one level of granularity this can be seen as a motion from one point to another. At a lower-level of granularity walking consists of the repeated movement of one leg after another. There is no natural lowest level of granularity where the motion can be seen as homogeneous.

Another problem with the existing research regarding granularity is that none of them appear to allow the switching between granularities. This is a difficult problem to overcome but has been examined by Hornsby and Egenhofer [2002].

Hornsby and Egenhofer [2002] have developed a model which allows the movement of individuals or objects to be represented over multiple granularities both in space and time. As they note, this method allows a user to uncover much more information about the movement in the data. In the proposed model, Hornsby and Egenhofer [2002] each individual's movement is modelled as a *geospatial lifeline* which is inspired by Hägerstrand's time geography [Hägerstrand, 1967, 1970]. Hägerstrand's time geography is a framework that analyses movement by using the paths of individuals as the basic constructs. Within Time Geography, all activities are considered to have a spatial and temporal dimension that cannot be 'meaningfully separated' [Miller, 2004]. The framework focuses on the relationship between the two dimensions for each activity and the constraints that space, time and the environment put on an individual's movement. Two concepts that are key to Time Geography are the *space-time path* and *space-time prism*. The former traces an individual's movement with respect to time; the latter represents all of the possible locations for a space-time path.

Like that of Laube et al. [2005] a *geospatial lifeline* within Hornsby and Egenhofer [2002] records the locations visited by the individual over a period of time. However with the model presented by Hornsby and Egenhofer [2002], the user can choose which level of granularity to observe the *geospatial lifeline* at. It is noted that movement is a continuous process which is usually observed through discrete time samples; Hornsby and Egenhofer [2002] relates the switching between different levels of granularity to the change of sampling rate. Depending on the level chosen, the lifeline will be modelled as a *lifeline bead*, a *lifeline necklace*, a *lifeline thread*, a *lifeline tube* or a *lifeline trace*.

A *lifeline bead* gives all the set of possible locations that an individual may have visited or passed through; this set is calculated according to the individual's given start and end points in space-time and maximum speed. Consisting of 'two inverted half cones', a lifeline bead allows us to analyse which locations might have been visited by an individual and for how long. Comparisons of the beads from two individuals can result in discovering periods when they might have met for a period of time whilst moving (two beads share a common part at the rim), whilst stationary (two beads intersect) and a point at which they met (two beads touch at the rim).

To refine the granularity that the lifeline is observed from, a *lifeline necklace* is observed instead of a single bead. The necklace arises from additional sample points being introduced into the model and consists of a sequence of beads. It is important to note that the end point of one bead will also be the starting point of the next bead. By examining the necklace, the locations that an individual visited can be refined. Since each bead is calculated based on the individual's maximum speed, comparisons of two beads within a necklace can help visualise changes in speed. For example, a wider bead would indicate a faster speed than that of a narrower bead.

To view the movement at a coarser level of granularity, Hornsby and Egenhofer [2002] present many methods. The beads in a lifeline necklace can be aggregated into 'fewer, generalised beads' or some selectively omitted. However, one could also move from viewing a necklace to a *lifeline thread*, a *lifeline tube* or a *lifeline trace*; each of these allows the model to be viewed at an increasingly coarser level of granularity. Retaining the start and end points of each bead in the necklace a *lifeline thread* is a 'linear approximation of an ordered sequence of space-time samples' which show the 'likely space-time points' that an object or individual may have visited whilst in continuous motion between two points. A *lifeline tube* is a 'shape-approximating approach' which approximates a necklace's geometry; a tube models the movement by taking the speed at the start and end points of the necklace along with point locations which have been selectively chosen from the rim of each of the necklace's beads. Derived from a tube (based on its center or 'biased towards the side of the tube'), a *lifeline trace* is the coarsest view that a lifeline can be observed from. Figure 4.3 depicts a lifeline trace, bead, necklace and tube.

4.6 Conclusion

The research that has been reviewed clearly highlights that a dataset can be considered as a set of spatiotemporal records each representing the position of an individual with the associated time for a given period (i.e., $\langle i, \overrightarrow{x}, t \rangle$ triples). Since each research project

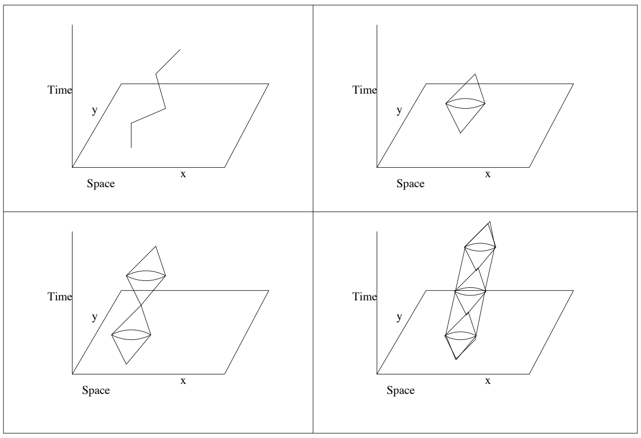


Figure 4.3: An example of a lifeline trace (top left), lifeline bead (top right), lifeline necklace (bottom left) and lifeline tube (bottom right).

requires different types and aspects of motion to be considered, it is unlikely that there will be a consensus as to how movement should be conceptualised. A number of possible proposals have been reviewed but no single method appears to exist that is capable of identifying the full range of collectives identified in Chapter 3. However, concepts used within the method could prove useful when considering a new, more suitable method.

The use of primitives and episodes are useful concepts [Mountain and Raper, 2001a,b; Dykes and Mountain, 2003; Dodge et al., 2008; Wood and Galton, 2009b]. However, when a group of moving objects is being considered, the movement parameters should be defined in relation to the movement of other moving objects in addition to being considered in relation to an external referencing sense (i.e., adopting both relative and absolute views). This consideration is noted by Dodge et al. [2008], although, it would appear that they only consider movement parameters in an absolute sense. Mountain and Raper [2001a] notes that the interactions between groups of individuals need to be considered in relation to 'significant events in space and time that affect behaviour'. The possibility of connecting user profiles is suggested as a way in which this can be done and the current work extended.

The inclusion of 'semantic' information could be problematic if it requires additional information to be recorded about the moving object rather than just the positions and associated time steps. For example, Spaccapietra et al. [2008] and Yan [2009] note that it may be necessary to record specific semantic properties such as place names or the type of activity that is being observed if semantic annotation is to take place. It may not be possible to guarantee this is included within a dataset. The model proposed by Yan [2009] assumes that the raw data comprise a set of position-time pairs but with no semantic data except the identity of the object that is exhibiting the movement patterns. After the raw data has been cleaned and any missing positions interpolated, the trajectory data are computed; the overall path of the moving object is split into 'meaningful segments' each of which forms a trajectory. The identification of beginning and end points can lead to an automatic segmentation algorithm being developed. This method is similar to the use of episodes. However, the definition of trajectory given by Spaccapietra et al. [2008] and

Yan [2009] requires a movement pattern to have a constant goal throughout the trajectory. Although many collectives exist where the individuals have a common or individual goal, it may not be possible to extract this information from the dataset or in advance.

For the work presented by Eftimie et al. [2007], three internal factors were sufficient but it is unclear whether these interactions alone could be used to develop a model that would explain the movement of a wider range of collectives. It also seems unlikely that the four types of movement patterns defined by Eftimie et al. [2007] are exhaustive enough to define all types of collective motion. The effects of variable membership and external factors would also need to be considered when analysing collective motion; as noted by Ali and Moulin [2005] and Sumpter [2006], the external factors which come from the environment which the collective exists in is very important and will affect the collective's motion.

Many of the generic movement patterns that are defined by Dodge et al. [2008] are relevant to collective motion. For example, *spatial concentration*, *synchronisation*, *repetition*, *co-incidence*, *constancy*, and *concurrence*. The taxonomy proposed by Dodge et al. [2008] acknowledges the possibilities of fixed or variable membership by qualifying their movement patterns *meet* and *moving cluster* by means of the additional attributes *fixed* and *varying*, which refer to whether the membership of the group can change. The difference between a meet and a moving cluster is that the former stays within a stationary region over the period of its existence whereas the latter follows a trajectory through space. However, there are examples of collective motion that have not been included. For example, a football match involves two teams (i.e., two collectives) interacting with each other. The movement patterns exhibited by each team arise primarily from its collective purpose of winning the match, but the spatial patterns involved in winning the match are oppositely oriented for the two teams. The resulting complementarity of the movement patterns forms a new type of movement pattern in its own right, not present in the classification presented by Dodge et al. [2008].

Lack of movement is also an important movement pattern which is missing. Consider a traffic jam where no traffic is moving; the lack of movement could indicate that the roads been blocked by something such as an accident. Another example is an orchestra during a performance. In the proposed taxonomy, Dodge et al. [2008] defines *meet* as a movement pattern consisting of a 'set of MPOs [moving point objects] that stay within a stationary disk of specific radius in a certain time interval . . . a stationary cluster'. This could be suitable for describing the movement of an orchestra whilst they are performing, but it could also describe a football team during a match — the taxonomy is not capable of distinguishing between these two very different types of collective: one where the individuals exhibit a wide variety of movement within the fixed region which they are confined to, and another where movement is largely absent.

The multiple entities that Andrienko and Andrienko [2007b] are concerned with analysing are those which retain their identity whilst changing their positions in space; the phenomena that are being considered within this thesis could be viewed in this way. However, no consideration is given to entities that can merge or split. This is an important feature of some types of collective. Consider a flock of birds — a phenomenon which can be seen daily. During flight the flock of birds may split into two groups but we might still refer to them as the same flock; it may be because the two sub-flocks will eventually merge to become one entity.

Clustering and aggregation are two approaches that could allow the presence of a collective to be highlighted within a movement dataset. Huang et al. [2008] take into account the importance of membership changes but not the movement of the overall collective. Aggregation may not be able to extract the necessary information from a dataset that the general taxonomy of collective requires (e.g., regarding an individual's role or source of coherence).

In conclusion, the research that has been reviewed within this Chapter has highlighted some important concepts and methods that would be relevant to a wider range of collectives. Examples include the use of primitives and episodes to conceptualise motion, and the use of clustering and aggregation aggregation to identify the presence of a collective. However, there are important examples of collective motion such as merging, splitting and the effects of variable membership that have not been sufficiently accounted for in the reviewed literature.

5 Identifying a Collective within a Dataset

The overall aim of the research presented here is to develop a method that allows the presence of a collective to be identified within a movement dataset. A review of existing research (Chapter 4), found definitions of movement patterns that relate to specific collectives such as flocks and herds [Gueron et al., 1996; Benkert et al., 2006] or particular domains [Thériault et al., 1999]. However, no research appeared to exist that was able to identify the wide range of collectives outlined in Chapter 3. Taxonomies of movement patterns have been developed that directly or indirectly related to collective motion, but these focus on the level of the individuals, resulting in important information being lost about the collective when considered as a single entity. Clustering and aggregation were two possible approaches that were identified as methods that may be capable of identifying the presence of a collective within a dataset. However, it was not clear how the information that the general taxonomy of collectives requires (e.g., role) could be obtained.

If a collective is to be identified from the movement that is exhibited by its members two possible approaches could be used. One approach would be to define the movement patterns that are exhibited by each type of collective. A wide range of collectives have been identified in Chapter 3 and, ideally, it should be possible to identify many, if not all, of these types of collective from their movement patterns. However, defining the movement patterns that are common to each and every type of collective would be very time consuming – only a small subset of the different types of collective appear to have been researched so far. An alternative approach, and the one that has been adopted here, is to establish the hallmarks of the class of collectives in general. Once a group of individuals have been highlighted as a possible collective, a taxonomy similar to the one presented in Chapter 3 could be applied to the group to identify what type of collective they form. This chapter will focus on the first part of this approach: identifying the presence of a collective within a dataset.

The taxonomy presented in Chapter 2 illustrated that a collective can have multiple sources of unity. Given the wide range of possible sources of unity, it is a very ambitious goal to identify the hallmarks of the full range of collectives. The focus of this work is to allow the presence of collectives to be identified within a dataset. For some collectives, their unity can result in spatially coherent behaviour; this feature of these collectives can be used to identify their presence within a dataset. Therefore, a restriction will be made to identify collectives that exhibit this feature, they will be denoted as *spatial collectives*.

It is important to note that spatiality does not characterise a particular subclass of collectives: rather, collectives of many different types may exhibit spatially coherent behaviour at some point during their existence. As an example, consider an orchestra which regularly comes together to perform or rehearse: the underlying ground for considering this as a collective lies in an overall collective purpose to perform music; when they come together to do so they will exhibit spatial coherence, but the orchestra still exists as a collective in the intervals between successive meetings, and at those times the individual members will be independently going about their day-to-day activities exhibiting no spatial coherence. This example also illustrates that some collectives will only be spatial collectives at certain times during their lifespan. These cases occur with collectives which, although their primary source of unity is non-spatial, do intermittently exhibit spatially coherent behaviour.

In Chapter 2 the concept of a unity criterion was discussed: a criterion that allows the members of a collective to be defined. The task of identifying collectives thus becomes one of determining whether or not appropriate unity criteria are satisfied. This approach could be used to identify spatial collectives within a dataset given only the movement patterns of their individual members. In order to do this, the spatial features which reflect or express unity criteria for spatial collectives need to be established. A review of existing research and an examination of a range of collectives has led to the identification of three such features, which will be referred to as *spatial coherence criteria*. If some set of individuals satisfy at least one of these criteria, they may be considered as forming, prima facie, some kind of spatial collective. The use of the term unity has been avoided since the spatial coherence that is being used to identify the spatial collectives are not necessarily their source of collectivity.

Before outlining the method which will be used to identify the presence of a collective, the types of collective that can be identified using movement pattern analysis are defined (section 5.1). During the development of the method, a set of assumptions were made about the movement pattern data that the criteria will be applied to; these assumptions are laid out in section 5.2. The possible ways in which a collective can manifest itself within a movement pattern dataset is detailed in section 5.3, which has lead to the definition of a set of spatial coherence criteria (section 5.4).

5.1 Spatial Collectives

Given that spatial collectives are a special case of collectives in general, in the sense that they have only been singled out since they exhibit a certain feature, they inherit many of the features described in Chapter 3 as pertaining to the wider class. However, when defining collectives in Chapter 3, a collective was required to have at least one member in order to exist; at some time the collective would require more than one member. However, since spatial collectives manifest themselves through spatial coherence, which cannot be be applied unless at least two members are present, it will be assumed in practice that any spatial collective must have two or more members. In the light of this features relating to membership must be reconsidered in the spatial case.

The important relation that exists between a collective and its members has already been discussed (Chapter 3); this relation represents one way in which the nature of collectives can be characterised. However, the way in which the members of a collective are identified must also be defined. For example, some individuals may simply be passing through a crowd that are watching a street performer; they do not consider themselves as part of the crowd but how should the individuals who are members of the crowd be identified without including the individuals who are just passing through? This is an example of where spatial coherence can distinguish between the collective and the wider group of individuals. Another example is the flow of two-way traffic on a road which allows cars to travel south or north. The direction of the individual cars can determine which collective they belong to: the collective of traffic travelling north, and the collective of traffic travelling south.

5.2 Movement Pattern Datasets

There is a wide variety of technologies that are capable of capturing movement data, each of which may record the data in a slightly different way. This section discusses the assumptions that have been made about the datasets that the coherence criteria will be applied to.

5.2.1 Structure and Content

Since this research focuses on the identification of spatial collectives, only datasets that comprise the movement patterns of groups of individuals will be examined; datasets that record multiple journeys of a single individual will not be considered.

Movement pattern data contains information about the positions of each object at given time steps. This data is likely to be structured in some way; an assumption will be made that a dataset will comprise a collection of $\langle i, \overrightarrow{x}, t\rangle$ triples, where i is the identifier for an individual, and $\overrightarrow{x}$ is the position vector of that individual at time t. This structure assumes that the identity of each individual is known. This may not be true for all datasets; for example, a dataset may record, at each time step, the positions that are occupied by the individuals that are being tracked but exclude the identity of those individuals (i.e., records comprising $\langle \overrightarrow{x}, t\rangle$ pairs). A discussion of this problem can be found in Chapter 9.

5.2.2 Preprocessing

The movement pattern data could be considered as a series of *snapshots*, where each snapshot is an inventory of the locations of all individuals that exist at a particular time step. This is a similar approach to that adopted by Huang et al. [2008]. However, the sampling rates at which the positions of the individuals are recorded may or may not be uniform (i.e., the same for each individual). For example, the position of one individual may be recorded every three seconds and another every four seconds; if the recording of the data is event driven, the sampling rates may be irregular. Whether or not the snapshots are meaningful will depend on the sampling rate.

If a dataset is to be considered as a series of meaningful snapshots, the positions of each individual must be known at a fixed set of time steps. If this is not true of a dataset, and a uniform sampling rate has not been used, a process of interpolation would be required to calculate any missing values and therefore obtain the necessary set of snapshots. It is assumed that, before the set of coherence criteria are applied, all necessary interpolation has been applied. It is important to note that different interpolation methods are possible [Pfoser et al., 2000]. It is not possible to say definitively which method should be used, but it is assumed an appropriate method is available.

Any data that is collected via GPS technologies will contain some error. It is assumed that the raw data will need to go through some form of cleaning process as suggested by Spaccapietra et al. [2008]; Yan [2009]; interpolation may be an aspect of this. However, the error that may exist in a dataset will also have to be taken into consideration when performing any computations using the data. A discussion of handling errors that exist within GPS data can be found in Chapter 7.

5.2.3 Spatial and temporal assumptions

Time and space are essential components of movement. Thériault et al. [1999] base their proposed taxonomy on a set of spatial and temporal assumptions:

1. time is defined as the set of measured times that is isomorphic to the set of real numbers;
2. temporal intervals delimit the lives of geographic entities;
3. geographic entities are assumed to be partially ordered in the time dimension;
4. both absolute and relative views of space are adopted;
5. a discrete representation of geographical entities in space and time is assumed;
6. the measurement units for space and time are chosen according to the application.

Many of these assumptions seem reasonable; however, some could be questioned. It is important that temporal information is incorporated into a system dealing with geographic information [Langran, 1992]. Assumption 1 seems to imply that all real-numbers can be measured; since all measurement has a finite degree of precision, this assumption is unjustified. As discussed in section 4.5, the way in which motion is described is dependent on the granularity at which it is observed. Assumption 6 requires the user to select the spatial and temporal measurement units that are most suited to the geographic scale and granularity necessary for their application[1]; but this would make it difficult, if not

[1] Although this seemed clear in the paper, discussions with Prof. Claramunt have indicated that this was not the authors' intention. However, further work by Prof. Claramunt and his colleagues has begun to address the problem of granularity [Thériault et al., 2002; Vandersmissen et al., 2009].

impossible, to consider the movement over multiple levels of granularity. Dodge et al. [2008] make a similar point.

For this research, it is assumed that the movement of an individual is observable at multiple levels of granularity. The user may choose an initial granularity level but this should not be fixed throughout the rest of the application the user must be able to change the level to see if different movement patterns, or spatial collectives, become apparent. This is crucial when reasoning about both movement [Hornsby and Egenhofer, 2002] and collectives [Wood and Galton, 2009a]. It should be noted that the finest level of granularity at which a movement pattern can be observed will be defined by the level of detail that has been recorded; this is dependent on the sampling rate.

There are many ways in which space and time can be represented [Peuquet, 2002]. Three possible approaches include a time-stamped approached (Huang et al. [2008] and Worboys [1994]); an event-based approach (e.g. Peuquet [1994], Claramunt and Thériault [1995], Worboys [2005] and Hornsby and Cole [2007]); and, an activity-based approach (e.g., Hägerstrand [1970] and Hornsby and Egenhofer [2002]); a more detailed review of these approaches can be found in Hornsby and Yuan [2008]. As already stated, the data will be viewed as a series of snapshots (i.e., a time-stamped approach). In accordance with assumption 4 of Thériault et al. [1999], both an absolute and a relative view of space will be adopted in the method proposed in this Chapter. As noted by Dodge et al. [2008], when considering groups of moving individuals it is important to take into account the position of individuals in relation to each other (a relative view) as well as their location in space (an absolute view).

Currently the movement of individuals is only considered in two dimensions; elevation is not considered.

5.3 Forms of spatial coherence

To highlight possible spatial collectives within a dataset, the typical forms of spatial coherence that are exhibited by the individual members need to be established. These features will be used to form a set of coherence criteria; if a group of individuals satisfy at least one of these criteria, they will be highlighted as a possible spatial collective.

An examination of the motion exhibited by the different types of spatial collective has identified three forms of spatial coherence: common location, similar movement parameters, and formation; each of these is discussed below. The criteria have been chosen because they appear to allow many spatial collectives to be identified within a dataset. It is important to note that these criteria are only used to indicate the possibility of a collective; particular spatial collectives may exhibit one or a combination of these criteria. If a collective satisfies more than one of the criteria, it could be argued that it exhibits a stronger degree of collectivity.

There are clearly dependencies between the three forms of spatial coherence, and this may result in certain types of collective being identified. For example, consider a platoon on the march. They will continue to share a common location but also maintain the same relative positions to each other (i.e., formation) and therefore, similar movement parameters (speed, distance and direction); by contrast, a crowd of people milling about aimlessly may exhibit common location but no common movement pattern or formation. Further discussion on this can be found in section 5.4.1.

5.3.1 Common Location

The individuals whose movement patterns are being examined are being observed over a time interval which contains multiple time steps. At any of these time steps, a group of individuals may be observed as occupying, at a certain granularity, the same location. If observed as sharing a location at more than one time step, that group could be considered as exhibiting a form of spatial coherence. The location which is shared could be referred to as a common location. Of course this does not mean that the individuals are occupying exactly the same position in an absolute sense; rather, their positions fall within a sufficiently small region that, at the granularity under consideration, they can be considered as co-located. It is stated that a location should be shared at more than one time step otherwise its coherence could be questioned. One could argue that a duration of three time steps should be considered and, in some cases (e.g., when the sampling rate is very frequent) this may be more suitable see section 5.5 for further discussion on this point.

Distinctions can be made according to the frequency of common location and the identity of that location. Some spatial collectives will always share a common location; a further distinction could be made between those spatial collectives that always share the same common location and those where the common location varies. For example, a platoon on the march will always share a common location. However, that location will change as they march from one place to another. In contrast, the trees in a forest will always share the same common location, when considered over a reasonably short period, since the trees are unable to move.

As noted in the introduction to this Chapter, some collectives exhibit intermittent spatial coherence. The members of an orchestra or a committee will repeatedly converge at a meeting place for a given time period to perform, rehearse or meet. At those times, they will exhibit spatial coherence by sharing a common location. However, when they are not meeting, the individual members will be going about their day-to-day tasks and are unlikely to occupy the same location. The pattern of repeatedly coming together to share a common location is an important form of spatial coherence – it is also a distinct pattern that is exhibited by certain collectives. Spatial collectives of this type can be distinguished further by looking at whether or not the common location that is shared is always the same or varies. Contrast a University cohort and a reading group. The former are likely to regularly converge on the University campus; the members of a local reading group often take turns in hosting a session: they do not always share a common location but, when they do, the location varies according to which member of the group is hosting the session. How regularly or intermittently the individuals occupy a common location could distinguish between the different types of collective that exhibit these patterns (see

Chapter 9 for further discussion on this).

Patterns such as *co-location* [Andrienko and Andrienko, 2007b; Dodge et al., 2008], suggest that common location may not always occur synchronously; a group of individuals could each visit a location in turn. For example, a tour group that splits up to visit each attraction. Therefore, *lagged common location* could also be considered. Other examples of co-location could include a tour group that is split into two to be guided around a city, or a group of treasure hunters. Each will need to visit the same locations but will not necessarily do so at the same time. It is clearly much more straightforward to detect synchronous (i.e., unlagged) common motion than lagged common motion, but the latter will be important in some applications.

Although the concept of a common location has been defined, what is meant by the term location must also be established. As noted above, it is unlikely that two individuals can occupy exactly the same position at any one time step. Therefore, common location is defined not as having the same position but as having positions falling within a specified area. There are many possibilities as to how these areas can be determined, two of which are outlined below.

For simplicity the space could be partitioned into grid squares, where each square counts as a unique location. How many squares make up a grid will depend on the granularity that the data is being presented at. The size of each grid square will depend on the individuals that are being considered and the level of precision that the data has been recorded at. A square needs to be large enough to allow more than one individual to occupy it; ideally it should be possible to capture entire collectives within a location. To detect very large collectives, larger grid squares will be needed. However, this approach does seem quite crude; if a collective is centred on a grid line, it will not be recognised as one collective. A preferable solution would be to use a sliding window, an approach that could be seen as enveloping (section 4.1); the overall space can be split into a grid (e.g., 1000×1000), and then a sliding window (e.g., 10×10) implemented. For each snapshot, the window could move from left to right moving one grid square at a time. On reaching the end of a row, it would move up one grid square and repeat the process until the whole space has been covered. Although computationally expensive, this would identify areas that contain possible spatial collectives without the restriction of grid lines. Figure 5.1 illustrates the first position of the sliding window (shown in grey) within the search space: WS refers to the value that is given by the user to define the size of the sliding window. The minimum values for both the x and y coordinates of the search space are used as an initial starting position of the sliding window (i.e., its bottom left hand corner).

A second approach to identify a common location, could be to analyse an area around each individual to see if there are any other individuals within a certain proximity. For example, figure 5.2 depicts three individuals: A, B and C at two different snapshots. The search radius for each individual is illustrated by the grey circle and denotes the proximity that two individuals must be within to be considered to share a location. In the first time step (depicted on the left), no individuals are within the required distance to satisfy the criterion; however, in the second time step (depicted on the right) individuals A and B

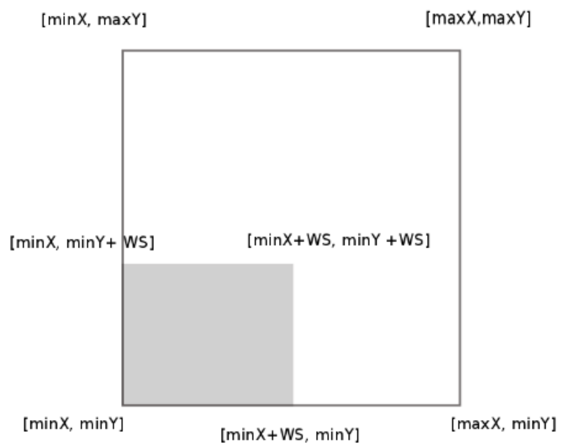


Figure 5.1: An example of a location-based implementation.

are.

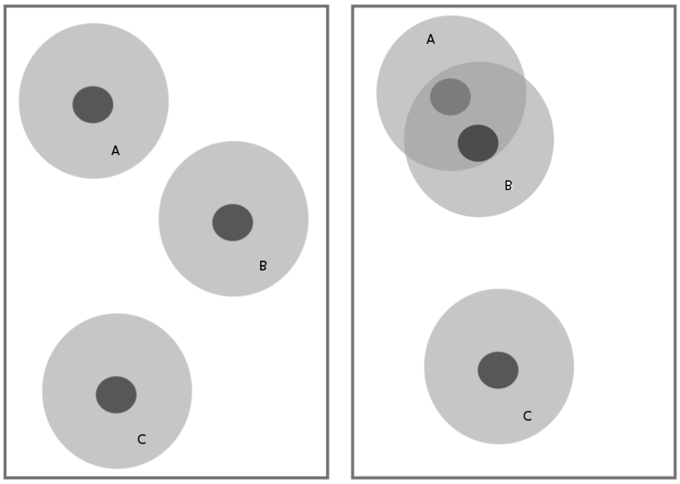


Figure 5.2: Considering common location using an individual-based approach.

The two approaches that have been suggested highlight two distinct ways in which a common location can be considered: from a location-based view or an individual-based view. The former analyses each location (i.e., each grid square) to see if it is shared by multiple individuals. The latter looks for groups of particular individuals that share a common location. These two views are subtly different and could detect two different types of spatial collective. For example, the crowd watching a street performer all share a common location but this collective will only be highlighted if a location-based view is adopted; the individuals participating in a crowd are likely to change on a regular basis and would not be picked up if an individual-based view is adopted. In contrast, a platoon on the march will only be picked up if an individual-based view is adopted the location shared by the soldiers is likely to vary from one time-step to another and therefore would not be shown as spatial coherence if a location-based view is adopted. Therefore, this coherence criterion should be applied using both location and individual-based views. These two views could be compared to *Eulerian* and *Lagrangian* motion. A Lagrangian view of motion focuses on the object that is moving (i.e., similar to the individual-based view); a Eulerian view of motion focuses on a 'fixed frame in space through which the motion occurs' [Maidment, 1993] (i.e., similar to the location-based view of common location).

The inclusion of a human analyst is fundamental for much movement pattern analysis [Andrienko and Andrienko, 2007b]. For this criterion, the user may initially set the grid squares, sliding window or distance between individuals, to be reasonably large and adjust the size if they feel that information is being lost. If the coherence criteria are being applied to a specific domain, the user may wish to set the most appropriate input for each of the three outlined implementation methods.

This criterion is clearly subject to temporal granularity as well as spatial granularity. For example, if a group of individuals come together only once for a period of one time step during the observation period, the group will not be considered as a spatial collective. Even if the group does come together regularly, the observation period is not long enough to capture this information. A group of individuals may be participating in a spatial collective but are only in a common location for one time step – the sampling rate may be so infrequent that one time step actually represents a large period of time. In the first case, where the observation period was too short to capture the information, little can be done. The research presented here is trying to identify the presence of a spatial collective given the input data and the observation period. The latter case illustrates another example where the inclusion of a human analyst is important. The analyst could identify that the sampling rate is too low and investigate whether any preprocessing (e.g., interpolation), can take place to allow for more collectives to be identified; the danger here is the production of fictitious collectives as an artifact of the sampling and interpolation processes.

5.3.2 Movement Parameters

Occupation of common locations, in one of the ways identified above, provides a *prima facie* indication of the presence of a collective within a dataset. However, common location alone may arise coincidence without being indicative of genuine association. Therefore, to refine the search for collectives, other markers of collectivity must be included within the set of coherence criteria. Speed and direction of each individual can be computed from a dataset. Possession of similar values for one or both of these parameters is a form of spatial coherence, which may indicate collectivity, especially if this is already indicated by common location. Therefore, the second coherence criteria will identify groups of individuals that have similar movement parameters, namely speed and direction; these are two of the parameters that were used to identify patterns in the REMO concept [Laube et al., 2005].

The direction of an individual can be considered in two different ways: in relation to the background within which the movement takes place; and, in relation to some designated point or individual. These two interpretations will be referred to as *absolute direction* and *relative direction* respectively. Individuals moving with the same absolute direction follow parallel trajectories. Given the definition of relative direction, three possible types of common relative direction could occur:

- A group of individuals all moving towards a given point, line or area.
- A group of individuals all moving away from a given point, line or area.
- A group of individuals all moving around a given point, line or area.

Each type of common relative direction has three possible alternatives depending on whether the motion is in relation to a point, line or area; it is important to note that a point could refer to an individual and a line or area refer to a group of individuals. The resulting nine types of common relative direction could themselves have two variances depending on whether the point, line or area that the motion is in relation to, is stationary or moving. The types of common relative motion give rise to characteristic movement patterns such as convergence, divergence, and revolution; they could also be typical of certain types of collective as discussed in Chapter 9. Figure 5.3 shows three examples of common relative direction: a group of individuals moving towards a point, a group of individuals moving away from a point and a group of individuals moving towards a line.

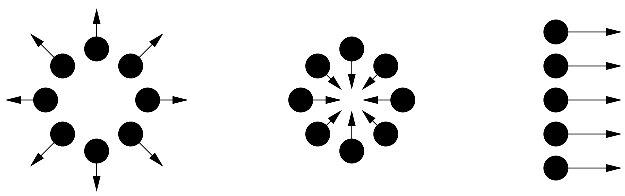


Figure 5.3: Three examples of ways in which common relative direction could occur with a group of individuals (moving towards a given point, away from a given point and towards a line).

Each of the movement patterns that have been defined can exist in two forms, *synchronous* and *lagged*. Consider the runners in a marathon; each individual follows essentially the same path, but they do not all do so simultaneously. Thus the sequence of directions followed by any two of the runners will be the same, but if one is lagging well behind the other, these sequences will not be synchronised. Similarly, in the case of convergence, it could be that all the individuals converge on the centre together, arriving simultaneously, or it could be that they arrive one after the other (e.g., children arriving for school). In the case of individuals revolving round a centre, if they do so as a compact group, or ranged along a radius vector, then this is just a case of parallel motion, since at any one time all the individuals will be moving in the same direction; if, on the other hand, they go round separately, then it is more like a case of parallel motion with time lag.

The common movement criteria search for similar, not exact, values, not only because GPS error must be considered, but also because members of a collective do not necessarily move at exactly the same speed or direction. The runners of a 100m sprint form a collective, and will move in the same direction, but they are unlikely to travel at exactly the same speeds. The user could be asked to define a percentage which states how similar two values must be in order for them to satisfy this criterion for their application. However, as with the previous criterion, they should be able to change this value when they consider it necessary.

There is a clear relation between this form of coherence and the previous one: a group that have been identified as occupying a common location or locations over a series of snapshots are likely to have moved in a similar direction and at similar speeds. However, this criterion may also indicate the presence of collectives that have not been identified as occupying a common location. For example, a pack of animals when hunting may split up to locate their prey; the individuals within a search party who are trying to locate a missing person will have similar movement patterns but may be placed in different areas of the region that they are searching.

5.3.3 Formation

The common location criterion allows for an absolute view of space to be considered. However, the position of the individuals in relation to each other must also be considered (i.e., a relative view of space) [Dodge et al., 2008]. Therefore, a third criterion will also be considered, formation, which detects whether a group of individuals maintain their relative positions to each other. This is closely related to the common relative direction criterion considered earlier, which analyses the relative speed and direction of individuals, but is not exhaustively covered by it – this criterion focuses on the relative positions of each individual.

If a group of individuals remain together in the same spatial area then it is possible that they could be members of a collective. However, as well as staying together they may remain in a particular formation, as, for example, a platoon on a march or a tour group asked to walk in pairs. This is a stronger form of spatial coherence; only in some cases would it be picked up by a combination of common location and common movement.

To identify groups that maintain their relative positions to each other, the distances between each and every individual could be computed and compared between different snapshots. If the values are the same or similar, taking into account GPS error, then it is possible that the group is moving in a particular formation and exhibiting a form of spatial coherence. However, this approach would not detect those collective who are rotating. A group of dancers could be revolving around a central individual who remains stationary – in this case the individuals may retain the same formation. The distances between the individuals may stay the same but the angles between them will not. Therefore, an alternative approach is to calculate a vector which records the distance and bearing between each and every individuals. A group moving in formation may have similar distances and bearings. There are clearly different forms of formation: a group of individuals may retain the same distance between each other but their relative bearings vary; the bearings may remain constant but the distances change (e.g., divergence and convergence); or, both the distanced and relative bearings remain constant.

If a group is moving in formation, the individuals are likely to be exhibiting similar movement parameters (i.e., speed, distance and direction). However, one form of spatial coherence that will not be picked up is rotation. Consider the group of dancers revolving around the stationary individual. The individuals do not have have similar movement parameters and therefore, will not be picked up by the movement parameters criterion. If compact, they may be found to share a common location but they may not and the common location criterion would not detect the pattern of rotation.

5.4 The Coherence Criteria

From the previous section, if a group of individuals satisfy one of the following coherence criteria for a sufficient number of time steps, they will be considered as forming a possible collective.

- They share at least one common location during a given time interval:
  - the individuals always share the same common location,
  - the individuals always share a common location but that location varies,
  - the individuals intermittently share the same common location,
  - the individuals intermittently share a variable common location.
- Each individual has at least one similar movement parameter (speed or direction), considering both absolute and relative directions:
  - the movement parameter is shared simultaneously,
  - the movement parameter is not shared simultaneously (i.e., with time lag).
- The individuals within the group maintain their formation.

One could question whether or not a group of individuals that never exhibits a form of spatial coherence should be considered as a spatial collective. However, by definition a spatial collective must satisfy one of the three defined spatial coherence criteria. If a group of individuals do not satisfy at least one of the criteria (e.g., the group of domestic rabbits that are one year old, or a group on the website, Facebook), they may still be considered as a collective under the taxonomy presented in Chapter 3 but they cannot be considered as a spatial collective.

There exists descriptions of classes of people that superficially appear to be defined spatially (e.g., a group of individuals that have never visited Exeter). However, for a group of individuals to be considered as a spatial collective, those individuals must satisfy one of the defined spatial unity criteria (i.e., the coherence criteria). Even though a group of individuals have never visited a location, it does not mean that they share a common location or satisfy one of the coherence criteria. This does not mean that the term *never* cannot be used in a description of a spatial collective. For example, the group of individuals that have never left Exeter, could be considered to satisfy one of the unity criteria, common location, at one level of spatial granularity.

5.4.1 Dependencies

As noted throughout section 5.3, there are clear dependencies that exist between the coherence criteria. A collective need only satisfy one of the criteria to be identified as a possible collective; however, if they satisfy a combination of the criteria, that collective may be considered to exhibit a stronger degree of collectivity. Some collectives may satisfy all three criteria: a group of individuals share a common location, have similar movement parameters and maintain the same relative positions to each other. If a group of individuals always share the same common location and have similar movement parameters, it is likely that those movement patterns are shared synchronously and not lagged. However, this dependency may not exist if a coarse level of granularity is chosen to identify common location. If a group of individuals are moving in constant formation, those individuals must also have similar movement parameters and always share the same common location. It seems unlikely that individuals that have no formation (i.e., do not maintain their relative positions to each other), will also not have similar movement parameters.

Although spatial collectives may satisfy all of the coherence criteria, they might not. Indeed, the combination of criteria that are satisfied may also help to identify a collective's type. This point is discussed further in Chapter 8.

5.5 Conclusion

As illustrated in Chapter 3, a wide range of collectives exist. Given the wide range of possible sources of unity it is too ambitious to develop a method capable of identifying all of these types of collective within a movement pattern dataset. Therefore, a restriction has to be made. A method has been proposed that identifies *spatial collectives*: collectives that manifest themselves in a movement dataset through spatially coherent behaviour. A set of coherence of criteria has been developed that identifies three different types of spatial coherence: common location, similar movement parameters and formation. If a group of individuals satisfies at least one of these criteria, they are highlighted as a possible spatial collective. Satisfying different combinations of the criteria could reveal different degrees of collectivity, or the type of collective that is present – these points have been left for discussion in Chapter 8. This chapter has outlined the criteria and given some indications of how they may be applied to a dataset. The following Chapter illustrates how the criteria can be applied to a synthetic dataset.

6 Implementing the Coherence Criteria

Spatial collectives are collectives that manifest themselves through spatial coherence and therefore, given a dataset that contains the spatiotemporal records of a group of individuals, the presence of these collectives can be highlighted by identifying those groups of individuals that are exhibiting some form of spatial coherence. Theoretical analysis has led to three different forms of spatial coherence being identified; these have been used to define a set of spatial coherence criteria (Chapter 5).

The success of the criteria in identifying the presence of a spatial collective, cannot be evaluated theoretically; instead, they must be applied to sample datasets. Therefore, the criteria have been implemented and applied, with the use of a specially designed computer program, to two different types of datasets: one synthetic and one real. This Chapter will detail how the coherence criteria have been implemented.

An overview of the program is given (section 6.1) including an explanation of how each spatial coherence criterion has been implemented (section 6.2). Section 6.3 explains what the computer program will output once the coherence criteria have been applied to a dataset.

6.1 Program Overview

Written in Matlab, the computer program comprises a set of functions that allow:

- a movement pattern dataset to be read in;
- the specified spatial coherence criteria to be applied individually or in combination using the necessary parameters that have been specified by the user;
- a user to see if any collectives have been identified and, if so, the coherence criteria that have been satisfied and the corresponding snapshots (i.e., timesteps);
- the user to reapply the coherence criteria with different input parameters.

It is important to remember that it is assumed the coherence criteria will be applied to a dataset that has a specific structure and certain properties (section 5.2). If this is known not to be true, the data must be preprocessed until the original assumptions are satisfied. Currently the program can accept two file types: *.csv* and *.xls*. Once the data has been read in, the user can apply one of the coherence criterion or a combination of the three.

The computer program has been tested thoroughly to ensure that when applied to a dataset, it is the spatial coherence criteria that are being evaluated and not the computer program. For each of the coherence criteria, each functional component was tested. For example, for the common location individual-based coherence criterion, it was important to ensure that the agglomerative clustering would stop once all individuals had been considered that were within the required distance threshold. Therefore, the code relating to agglomerative clustering was tested with sets of 'dummy data'; within each of these datasets, the distances between each and every individual were known. Within one test, a distance threshold was chosen that was larger than any distance between any two individuals within the dataset; this test correctly returned each individual as forming its own cluster. A second test was performed to see if one cluster was returned when all individuals within the dataset were the same distance apart and the distance threshold was larger than this distance; the test correctly returned one cluster. A third test was carried out to ensure that distinct clusters could be found with a suitable distance threshold. Similar tests were carried out with the remaining coherence criteria.

6.2 Implementation of the Coherence Criteria

The following set of coherence criteria were outlined in Chapter 5:

1. A group of individuals are found to share at least one common location during a given time interval. Individuals could share a common location at sufficiently many time-steps, either consecutively or intermittently; in both cases the common location may be constant or variable.

2. Each individual within a group is identified as having at least one similar movement parameter (speed or direction) at sufficiently many time-steps, either consecutively or intermittently; if considering direction, both absolute and relative directions may be considered. The common movement pattern could be shared simultaneously or with time lag.

3. A group of individuals maintain their formation (i.e., their relative positions) over a sufficient number of consecutive time-steps.

Similar to the taxonomy presented in Chapter 3, the spatial coherence criteria have been developed to identify salient qualitative differences. However, a computer program cannot automatically identify these type of differences; implementation of the criteria requires a more quantitative approach, where thresholds can be set to allow the computer to distinguish between what we denote qualitative differences. Therefore, for each criterion, there are some parameters that the user must set.

All three criteria take in a value for the cardinality constraint and the snapshot constraint which state respectively the minimum number of members a group must have to be deemed a spatial collective, and the number of snapshots that the criteria must be satisfied for; both of these values should be specified by the user at run time; similar inputs were used by Huang et al. [2008]. A snapshot constraint for the first and second criteria could be considered both intermittently and consecutively. However, for the third criterion, formation, the term *maintained* would suggest that the formation should only be considered consecutively. Two outputs will be given to the user, one stating the collectives that have satisfied the criteria over intermittent snapshots and those that have satisfied the criteria over consecutive snapshots. The inclusion of a human analyst is important (section 4.3); this has been taken into consideration when implementing the coherence criteria and the user can reapply the criteria with different values for the two constraints and visually compare the results if they deem necessary.

Each of the coherence criterion have been implemented using a combination of Matlab functions. Different ideas were presented within Chapter 5 on how each of the criteria could be implemented. The following sections will describe the approaches that have been adopted and how each criterion was finally implemented. The required input parameters for all of the criteria are summarised in table 6.1. A percentage is also required for the formation and similar movement patterns criteria. These two criteria are trying to identify individuals that have similar values for a certain parameter (e.g., speed or direction); the percentage represents how similar these two values must be.

Criterion	**Snapshot constraint**	**Cardinality Constraint**	**Other Inputs**
Common Location Individual-based	Intermittent, Consecutive	Yes	Distance
Common Location Location-based	Intermittent, Consecutive	Yes	Window size
Similar Movement Parameters	Intermittent, Consecutive	Yes	Percentage
Formation	Consecutive	Yes	Percentage

Table 6.1: The input parameters for the formation criterion

It should be noted that some of the criteria have not been implemented exhaustively (i.e., with all the ideas suggested in Chapter 5). As an initial step, it was decided to identify whether the coherence criteria in their simplest form could fulfil the aim of identifying the presence of a spatial collective; if found not to be sufficient, the criteria would then be expanded. Further discussion on further extensions to the implementation can be found in Chapter 9.

6.2.1 Common Location

Two different approaches were given in section 5.3.1 to identify a common location: a *location-based view* and an *individual-based view*. The former method focuses on specific locations with the aim of finding locations that are always populated by the necessary number of individuals for sufficient time steps (i.e., at least the cardinality and snapshot constraints). The latter approach focuses on individuals, looking for specific individuals that share a location over sufficient time steps and satisfy the cardinality constraint. The computer program implements both an individual-based view and a location-based view.

For a location-based view, the user is requested to input a search radius (i.e., a distance); if an individual is within another individual's search radius, those two individuals are considered to be close enough to be considered as forming a collective at that time step. Using the distance given by the user as an input, agglomerative clustering [Duda et al., 2001] is used to calculate whether any collectives exist in each snapshot, and if so, which individuals are their members. Agglomerative clustering initially considers each individual as forming its own cluster. Upon each iteration, the shortest distance that exists between two individuals is chosen and those individuals are merged into one cluster; if more than one pair of individuals are separated by the shortest distance, one of the pairs is selected at random. The process continues until the required number of clusters have been found; or, no clusters are within a distance threshold. Within the computer program, the distance that has been input by the user is used as this distance threshold.

Within the computer program, the distance between each pair of individuals is calculated for each snapshot; to discount the distance between a point and itself, the relevant values are set to infinity. Using the user's input as the distance threshold, agglomerative clustering is performed. Once all pairs of individuals have been considered that satisfy the distance threshold, the clustering is terminated and the clusters that have been identified are returned as a list of possible collectives – any candidate collectives that do not satisfy the specified cardinality constraint are discarded immediately.

Information obtained for each snapshot is collated to identify which groups have been identified in which snapshots. If any of these groups appear in the necessary number of intermittent or consecutive snapshots they are returned as the spatial collectives that have been identified through an individual-based view of the common location criterion. The use of a clustering algorithm to detect spatial collectives at each time step is similar to that adopted by Huang et al. [2008].

Two suggestions were made in section 5.3.1 about how a location-based view could be implemented: split the space into a grid where each grid square represents a location; or, adopt a sliding window. It was noted that the use of a grid was quite crude – if a collective was centred on a grid line, only where that part of the collective is located would be considered at any one time (i.e., when considering the grid square that that part of the collective is located). Taking this into consideration, a sliding window has been implemented.

The minimum values for both the x and y coordinates of the search space are used as an initial starting position of the sliding window (i.e., its bottom left hand corner). The window then moves from left to right by a percentage of the sliding window's dimensions until the edge of the space has been reached, at which point it moves up by the same percentage and begins the process again; the process is repeated until the entire search space has been considered. The user must input the size of the sliding window that they would like to adopt; since the sliding window is a square the user need only input one integer.

For each snapshot, the locations of the sliding window that have a sufficient number of individuals to satisfy the cardinality constraint, are recorded as a possible common location; any areas that do not satisfy the cardinality constraint are discarded. The computer program will compare the results obtained from each snapshot to locate any areas which satisfy the criterion for the necessary number of snapshots, consecutively or intermittently, and therefore, can be highlighted as satisfying the location-based view of the common location criterion.

Within section 5.3.1, four different types of common location were enumerated with distinctions between individuals according to whether or not they always share a common location, and, if that location is constant or varies. Currently, when applying an individual-based approach, the identity of the common location that is occupied by the individuals in a group is not recorded. This aspect of the criterion may allow the different types of spatial coherence concerning common location to be identified and therefore, the different types of collective that would exhibit this coherence. However, presently the focus of the coherence criteria is to establish whether they can successfully identify the presence of a spatial collective within a dataset, not necessarily its type – this is left to further research and is discussed in Chapter 9.

6.2.2 Similar Movement Parameters

This criterion compares the movement parameters, namely speed and direction, of every individual to identify those individuals that share at least one these movement parameters. Section 5.3.2 stated that the directions of each individual could be considered relatively (i.e., in relation to another individual or object) or, absolutely (in relation to the background in which the movement takes place). Three types of relative direction were enumerated depending on whether a group of individuals all move towards, away from or around a given point or individual.

As an initial step to identify the efficiency of the spatial coherence criteria, only absolute direction is considered; relative positions are considered within the formation criterion (section 6.2.3). To identify those individuals that share similar speeds and directions synchronously, velocity vectors are computed for each individual at each snapshot. Currently the absolute velocity is computed, as a vector, for each individual from time step n to $n + 1$; if deemed successful this approach could be extended to compute the relative velocity vectors for each pair of individuals thus identifying relative direction.

For each pair of time steps (i.e., n and $n + 1$), those individuals that are found to have similar values for velocity are identified. This is done by plotting the velocities of all individuals for each pair of time steps and using the sliding window approach presented in section 6.2.1 to identify those individuals that have similar velocities; similarity is defined by a percentage that is defined by the user (i.e., if the difference between two velocities is within that percentage, they are considered to be similar). Once groups of individuals have been identified for each pair of time steps, each and every remaining pair of time steps are analysed to see if any groups, that satisfy the cardinality constraint, also satisfy the snapshot constraint, either consecutively or intermittently.

A sliding window has been implemented as this allows similar values to to identified and not just those that are equal. As discussed within section 5.3.2, similar values must be extracted as opposed to exact values due to possible errors within the data and members not moving at exactly the same speed.

Within section 5.3.2, it was noted that individuals may have similar movement patterns synchronously or lagged (i.e., with time-gap). Currently the computer program does not identify individuals that have lagged similar movement parameters.

6.2.3 Formation Criterion

The formation criterion identifies if any groups of individuals, which satisfy the specified cardinality constraint, maintain the same relative positions to each other for the required number of snapshots. For each snapshot, the relative positions are calculated between each pair of individuals. The relative positions of each pair of individuals are then compared over all snapshots to see if any group maintain their relative formations (i.e., formation) for the necessary number of consecutive snapshots. Since this criterion focuses on whether or not a group maintains their relative positions, unlike the previous two criteria, it is assumed that the coherence must be exhibited over consecutive snapshots.

The relative position is computed as a vector recording the distance and bearing between every pair of individuals. The term *bearing* refers to the angle between two individuals when considered in an anti-clockwise direction. A matrix is returned which records the consecutive snapshots that the identified pairs of individuals have maintained their relative positions over. Simply returning the pairs of individuals that maintain their formation is not sufficient – some individuals may be common in more than one pair signifying collectives that comprise more than one member. Therefore the matrix is analysed to see if there are any common individuals in any of the pairs that have been identified for the given snapshots. This step must take place to establish whether there are any groups that maintain their formation but comprise more than two individuals. For example, table 6.2 shows five pairs of individuals that maintain their formation over a minimum of three snapshots. P_x represents an individual point, S_B and S_E represents the first and last snapshots respectively over which the formation was maintained. The table indicates that P_1 has been identified as maintaining formation between snapshots one and three with both P_2 and P_4, thus forming a possible collective. It could be noted that although P1 and P2, and P1 and P4, exhibit common formation, P2 and P4 do not – formation does not require equal values, only that they be 'similar'. If equal values were required, or 'similar' is considered transitive, then the collective would include P1, P2, P3 and P4. Therefore, as a potential spatial collective $\{P1, P2, P4\}$ could be considered weaker than it would be if P2 and P4 also exhibited common formation.

The computer program will only consider common pairs that occur within the same range of snapshots; this is necessary when trying to establish maintained formation over a

Individual 1	Individual 2	$\mathbf{S}_B$	$\mathbf{S}_E$
P_1	P_2	1	3
P_3	P_4	2	4
P_1	P_4	1	3
P_5	P_6	2	4
P_1	P_7	2	4

Table 6.2: An example of identifying collectives which comprise more than two individuals under the formation criterion.

range of snapshots. Once all common individuals have been established, a list of the groups that satisfy the criterion are returned along with a statement of the range of snapshots over which their formation is maintained.

6.3 Visualising the Results

For each criterion, the computer program will return the number of collectives that have been found consecutively and, where relevant, intermittently. Users may also visualise the results using the movies that are produced for each criterion. Movies depict the evolution of each and every individual's position over the entire observation period. During the period when a group of individuals have been identified as a spatial collective, the individuals within that group are represented using a different colour.

6.4 Conclusion

If the spatial coherence criteria were to be sufficiently evaluated, they needed to be applied to datasets. Therefore, a computer program has been developed that implements each of the coherence criteria.Chapter 5 had suggested many ways in which the criteria could be expanded. Each criterion was implemented in its most simplest form to establish if the method could identify the presence of spatial coherence criteria within a dataset.

Since a computer cannot automatically detect the qualitative differences used by the coherence criteria, a more quantitative approach was required: for each criterion the user must set parameters which are then used as thresholds by the computer to detect the differences that we refer to as qualitative. Each criterion also requires the user to specify a cardinality constraint and a snapshot constraint which respectively state the minimum number of members that a group of individuals must have to be deemed as a spatial collective, and the number of snapshots that the criteria must be satisfied for; where appropriate, both intermittent and consecutive snapshot constraints are considered. The computer program displays the results of applying the coherence criteria to a dataset in two ways: the number of collectives that have been found consecutively and, where relevant, intermittently is specified, and a movie is produced. Each movie depicts the evolution of each and every individual's position in the dataset over the entire observation period; individuals that have been identified as participating in a spatial collective are depicted in a different colour.

Chapter 7 presents the results of applying the coherence criteria, using the computer programmed that has been outlined in this Chapter, to two datasets: one real and one synthetic.

7 Applying the Coherence Criteria

To fully evaluate the method presented in Chapter 5, two datasets have been obtained: one synthetic and one real. This Chapter details the results of applying the coherence criteria, using the computer program outlined in Chapter 6 to each dataset.

A description of the synthetic dataset can be found in section 7.1; the results and evaluation of the criteria's application to this dataset can be found in sections 7.1.2 and 7.1.3 respectively. A description of the real dataset is given in section 7.2. Since the dataset did not satisfy the assumptions laid out in section 5.2, some preprocessing was necessary; this is detailed in section 7.2.1. After identifying the necessary parameters (section 7.2.2), each of the spatial coherence criteria were applied, the results are presented in section 7.2.3. The results from applying the coherence criteria to the two datasets are discussed in section 7.3.

7.1 The Synthetic Dataset

To test whether or not the coherence criteria can successfully identify a spatial collective, a set of three synthetic datasets have been produced that each contain 40 boid-like individuals [Reynolds, 1987] that each follow the three rules: separation, alignment, and cohesion; for each rule, a value of between 0 and 1 can be applied where 0 is very weak and 1 is very strong. Every dataset contains 400 time steps each comprising the identification and position of every boid. Every boid is present in each time step – new boids do not appear and old ones do not cease to exist.

Each of the three datasets has been produced using a computer program developed by Max Dupenois (University of Exeter); the program will produce a *.csv* file for each time step. Since the datasets that are produced satisfy the assumptions given in section 5.2, no preprocessing is necessary.

Within one dataset (SD1), 20 of the boids have much higher values of alignment and cohesion than separation (1, 1 and 0.3 respectively). The remaining twenty boids have a value of 0.33 for alignment and cohesion and 0.8 for separation. The former group of boids will be referred to as species A, the latter species B. Within the second dataset (SD2), two species still exist but species A have been given slightly lower levels for alignment and cohesion (0.6); species B retain the same parameters. A third dataset (SD3) has been created which contains 40 boids of species B. It should be noted that where two different 'species' of boids have been included, the settings of the parameters for both species have been chosen to favour the formation of spatial collectives in species A but disfavour them in species B. Therefore, few, if any, spatial collectives should be found in SD3. The values for each species were chosen through experimentation: test values were set for alignment, cohesion and separation and then a movie played to see how individuals with these settings behaved with regards to the formation of collectives. For SD1, species A was required to strongly favour the formation of collectives. Therefore, the highest possible values were chosen for alignment and cohesion. Within SD2, species A needed to favour the formation of collectives more than species B but not as strong as species A within SD1; values of 0.5 and below were found to be too low to favour the formation of collectives, values of 0.7 or higher were found to form similar collectives as those by individuals of species A in SD1. Therefore, for species A in SD2 a value of 0.6 was chosen for alignment and cohesion. Species B was not to favour the formation of collectives; therefore a reasonably high value for separation was required but low values for alignment and cohesion. The respective values of 0.8, 0.33 and 0.33 appeared to best fit these requirements.

Within the movies that are produced by the computer program, individuals of species A are represented by '+'; individuals of species B are represented with a 'o' – this can be observed in figures 7.1a, 7.1b, and 7.1c.

7.1.1 Finding the Correct Input Parameters

As noted within Chapter 4, the use of a human analyst is often crucial when trying to extract information from movement datasets; they can often visually detect when information is being lost during extraction. When applying the spatial coherence criteria to a dataset, the user must establish the optimum values for each of the parameters (table 6.1). Therefore, the coherence criteria were applied to an example of dataset, SD1, to find the optimum values of the parameters for each of the criteria. A parameter was considered to have an optimum value if, after viewing the movies that had been produced for each of the criteria, the user did not feel any information was being lost or too much information extracted. It is assumed that the user will normally have some understanding of what is being shown (e.g., like the ship specialist consulted in Chapter 7). With very large datasets, the user may not be able to obtain sufficient information via visual analysis alone (i.e., the movies); therefore, the matrices that are produced for each of the coherence criteria could also be used. However, the boid dataset is very small and this information is easily obtained through the movies. This approach could be considered subjective but is similar to that adopted within Andrienko et al. [2009].

Each criterion was tested with cardinality and snapshots constraints of 2, 3 and 4; each experiment used the same value for the two constraints. Where appropriate, a criterion's snapshot constraint was tested both intermittently and consecutively. In reality, the user is likely to have an idea of how many individuals their application domain would require to form a spatial collective; a user could also try each of the three values for the two constraints in combination (i.e., not have them the same). This approach was not adopted for the experiments since initial results appeared to indicate suitable values for the constraints (i.e., many of species A were identified as participating in a spatial collective but not members of species B).

Where a criterion took in a third input, different values were tested for this additional parameter in combination with the three different combinations of snapshot and cardinality constraint (i.e., with both set to 2, 3 and 4). The values of the additional parameters are affected by the snapshot and cardinality constraint; they must be large enough to allow for a certain number of individuals to be present within the window or the specified distance but not too large that unnecessary information is obtained. For a location-based view of common location, window sizes of 50, 60, 70, 80, 90 and 100 were tested as well as the percentage that the sliding window should be moved after each iteration. These values were not chosen arbitrarily: the size of the overall search space was taken into consideration. Distances of 1, 2, 3 and 5 were considered for an individual-based view of common location. For the formation and similar movement parameters criteria, different percentages were considered; these percentages represented how different the two values could be whilst still being considered as 'similar'.

The results of the experiments highlighted that a cardinality constraint of 2 was far too low – the spatial coherence criteria could not accurately identify only those individuals that should favour forming a collective (i.e., individuals of species A). Similarly, a snapshot constraint of 2 also seemed too low; this could be because the period represented by two snapshots was not sufficient to identify actual examples of genuine coherent behaviour; coincidental coherence was often picked up. A constraint of 4 for both the cardinality and snapshot constraints led to very positive results with no individuals of species B being identified as participating in a collective. However, the movies produced for each criteria indicated that groups of three were present within the dataset. Therefore, an optimal value of 3 was selected for the snapshot and cardinality constraints. Regarding additional parameters, a window size of 50 and distance of 4 were found to suitable for the common location criterion; a value was considered suitable if the majority of individuals that were being selected as members of a collective were of species A. Originally the sliding window was set to move along by ten percent of its width; however, it was soon discovered that this decreased running time and resulted in too much information being replicated. The movement of the window needed to capture enough information without replicating too much information or reducing running time. Therefore, after further analysis via experimentation, a value of forty percent was chosen. Since the boids were known to move in a similar way (i.e., they all are following the same rules but at slightly different levels for each species), small percentages were chosen for the formation and the similar movement parameters criteria, namely 1%. This value is very small and, for more practical applications (i.e., with real data) is unlikely to be suitable especially if GPS error had to be taken account of. However, given the synthetic dataset, 1% was found to be suitable.

7.1.2 The Results

Applying the spatial coherence criteria to each of the three datasets would not provide enough results to clearly show that the criteria could successfully identify the presence of a spatial collective within the dataset. Therefore, the coherence criteria were applied to sixty different instances of the three datasets (i.e., to sixty different datasets that each have the same settings as SD1, sixty different datasets that have the same settings as SD2 and sixty different datasets that have the settings found in SD3). To ensure that distinct datasets were used, the computer program that was used to generate the datasets was run continuously until a sufficient number of time steps were obtained. A single *.csv* file is created for each time step; the first 400 files were taken as the first dataset, the next 50 files were discarded and the following 400 taken as the next dataset – this process continued until sixty datasets had been obtained.

It is not appropriate to show the results, in detail, from each of the 180 datasets; however, the results from a dataset of type SD1 are given in detail for illustrative purposes. The remaining results can be found in tables 7.2, 7.3, and 7.4. When displaying screenshots from the movies that are produced to visually show the results of each criterion, individuals of species A are identified by '+', species B by 'o'. If they are found to exhibit coherence at a snapshot, the individuals are highlighted in red. The illustrations are provided to show the detection of spatial collectives by each of the coherence criteria and how a user can visually see this detection. Since species A within SD1 strongly favour the formation of collectives, it is therefore, the best dataset for viewing the collectives that have formed and which of the coherence criteria that has detected them. Since 60 different instances of dataset SD1 exist, the first dataset was chosen to be used to illustrate the results. It should be noted that this dataset was chosen without looking at its contents and that there were no criteria for choosing this dataset. The illustrations have been included simply to show examples of what is being output by the computer program. The particular dataset from which they come have accuracy ratings of 90%, 65% and 55% for common location (individual-based), formation and similar movement parameters respectively. A statistical analysis of the full set of results for all sixty datasets can be found in section 7.1.3. It should be noted that for the sample dataset the accuracy ratings for formation and similar movement parameters are lower than the averages given in section 7.1.3; here only 40 boids are being considered whereas the full set of datasets consider 2400 individuals. There is no reason that a randomly chosen dataset should conform to the averages for the full population.

Table 7.1 shows how many spatial collectives were identified for each of the criteria within the dataset; since no known common locations exist within the dataset, only the results from the individual-based common location are shown. C_C refers to collectives that satisfy a criterion over a sufficient number of consecutive snapshots, and, where appropriate C_I refers to collectives that satisfy a criterion over intermittent snapshots. S_x states how many of the individuals within species x (i.e., A or B) were identified under that criterion as participating in a spatial collective, either intermittently or consecutively.

Figures 7.1a, 7.1b, are two screenshots which depict the evolution of the individuals without any coherence criteria being applied (i.e., all individuals are represented by the same colour). Figure 7.1c displays the trajectories of the forty boids between the snapshots depicted in figures 7.1a, 7.1b.

For illustrative purposes, figures 7.2, 7.3, 7.4 and 7.5 show three screenshots from the

Criterion	C_I	C_C	S_A	S_B
Common Location: individual-based	7	9	17	1
Formation	-	49	16	10
Similar movement parameters	83	572	19	17

Table 7.1: The results of applying the coherence criteria to a dataset of type SD1.

movies produced when the coherence criteria were applied to the dataset of type SD1; a screenshot represents one snapshot. Individuals shown in red have been identified as satisfying the coherence criteria for that screen shot.

Tables 7.2, 7.3 and 7.4 gives an overview of the results that were obtained from applying the criteria to SD1, SD2 and SD3 respectively. Since the coherence criteria were applied to sixty different instances of each dataset, each value represents an average.

The datasets were developed to include a group of individuals whose parameters would favour the formation of collectives (species A) and a group that did not (species B). Since datasets of type SD1 and SD2 both have two species, one of which that have been given parameters that should favour the formation of collectives, it was expected that the coherence criteria should consistently identify more individuals from species A as being members of a collective; very few individuals of species B were expected to form spatial collectives. Since no individuals of species A exist within datasets of type SD3, very few, if any, individuals should be identified as participating in a collective. Since individuals of species A have higher values for coherence and alignment in dataset SD1 than SD2, one could postulate that more collectives would be found to exist within a dataset which contains individuals with higher values of alignment and cohesion.

If analysing the coherence criteria individually, the results presented in tables 7.2, 7.3 and 7.4, appear to indicate that the common location criterion, when adopting an individual-based view, accurately distinguishes between species A and B; where collectives are identified, their members are mostly of species A. This criterion also consistently identified no collectives within SD3. The location-based approach of the common location criterion cannot really be analysed with this data alone since it was not known if any locations existed within the data that should have been highlighted as a spatial collective.

The formation and similar movement parameters criteria do appear to identify more individuals of species A as participating in a spatial collective than individuals from species B. However, in contrast to the individual-based approach of the common location criterion, where there were no members of species A within a dataset, a reasonably large number of collectives were identified whose members came from species B, especially within the similar movement parameters criterion. Interestingly, more spatial collectives were identified within SD2 than SD1 under both the formation and similar movement parameters criteria.

Criterion	C_I	C_C	S_A	S_B
Common Location: individual-based	7	9	17	1
Formation	-	49	17	10
Similar movement parameters	83	572	9	0

Table 7.2: The results of applying the coherence criteria to 60 datasets of type SD1.

Criterion	C_I	C_C	S_A	S_B
Common Location: individual-based	1	0	11	1
Formation	-	52	18	9
Similar movement parameters	93	729	10	0

Table 7.3: The results of applying the coherence criteria to 60 datasets of type SD2.

7.1.3 Statistical Evaluation

The results that have been presented so far can lead to a high-level discussion of how successful the coherence criteria are in detecting spatial collectives within the synthetic dataset, however, to establish the accuracy and consistency of the criteria in identifying the presence of a spatial collective within the dataset, each criterion needs to be statistically analysed. Although there are no specific collectives that are known to exist within the dataset, it is known what individuals belong to what species. Therefore, statistical analysis will be used to examine how accurately the criteria can identify individuals of species A as being members of a collective – it is known that the parameters of species A should favour the formation of collectives.

For each of the 60 iterations of applying the criteria, it was recorded whether an individual was considered to be a member of species A or B; an individual was considered to be of species A if it had been identified as participating in at least one collective for that criterion. A confusion matrix was produced for each iteration of the criterion to show how many individuals had been correctly or incorrectly identified as being a member of species A or B; no individuals are identified within the common location (location-based) criterion and therefore, the results from this criterion are omitted from the following analysis. A confusion matrix can be used to compare the number of correct classifications and predicted classifications in a classification system; a sample confusion matrix is shown in figure 7.5. For the classification system being analysed here, TP (*true positive*) and TN (*true negative*) refers to the number of individuals that have been correctly classified as species A and B respectively. FP (*false positive*) and FN (*false negative*) respectively denotes how many individuals have been incorrectly identified as species A and species B.

For each dataset, three confusion matrices were produced, one for each of the criterion. The resulting 9 matrices are presented in figures 7.6, 7.7 and 7.8; each matrix represents an average of the application of the criterion to the sixty different instances of that dataset. The values within each confusion matrix are percentages and denote the true positive, false positive, true negative and false negative rates.

Criterion	C_I	C_C	S_A	S_B
Common Location: individual-based	0	0	-	0
Formation	-	31	-	23
Similar movement parameters	76	411	-	8

Table 7.4: The results of applying the coherence criteria to 60 datasets of type SD3.

		Identified	
		A	**B**
Actual	**A**	TP	FN
	B	FP	TN

Table 7.5: A Confusion Matrix

To analyse the confusion matrices, three statistical measures were computed: accuracy, precision and recall. Tables 7.6, 7.7 and 7.8 show the associated values for accuracy, precision and recall. For reference, accuracy refers to the fraction of all identifications that were correct.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is the fraction of positive identifications that are correct.

$$Precision = \frac{TP}{TP + FP}$$

Recall is the fraction of species A that were correctly classified.

$$Recall = \frac{TP}{TP + FN}$$

	SD1	**SD2**	**SD3**
Accuracy	87.13%	87.96%	50%
Precision	79.88%	83.37%	0%
Recall	99.25%	94.83%	0%

Table 7.6: Common Location Performance Analysis

	SD1	SD2	SD3
Accuracy	76.75%	79.59%	44.80%
Precision	68.62%	72.22%	46.48%
Recall	98.58%	96.17%	99.50%

Table 7.7: Similar Movement Parameters Performance Analysis

	SD1	SD2	SD3
Accuracy	73.67%	73.92%	51.38%
Precision	67.03%	67.78%	50.10%
Recall	93.17%	91.17%	73.08%

Table 7.8: Formation Performance Analysis

Common Location

Table 7.6 indicates that this criterion had reasonably high accuracy and precision scores for SD1 and SD2. This criterion consistently identified no collectives within SD3, and this is highlighted within the true positive, false positive, true negative and false negative rates shown in figure 7.6. For both SD1 and SD2, high true positive rates (99.25% and 94.83%) and reasonably high true negative results (75% and 81.08%) were obtained. It would appear that the settings given to species A did cause the occasional member of species B to be highlighted as a member of a collective. However, this criterion is correctly predicting a large number of species A with recall scores of 99.25%, 94.83% and 0%; note that there were no individuals of species A within SD3 and, therefore, a recall of 0% is very good (i.e., no individuals were identified as being of species A).

Formation

Many of the scores are not as high for this criterion than those obtained by the common location criterion. This may be because the general behaviour of boids do tend to cause some degree of alignment. However, the proportion of individuals who have been incorrectly as species A (i.e., the false positive rate) is still low for datasets SD1 and SD2 (45.83%, 43.33% respectively). The false negative appears to be very high for SD3 (70.33%), but it must be remembered that the confusion matrix was trying to identify two species within the dataset even though no individuals of species A were present. The proportion of individuals who have been incorrectly classified as B is low (6.83%, 8.83% and 26.92%).

Similar Movement Parameters

This criterion has high scores for the true positive rate (98.58%, 96.17% and 71.67%) and precision (68.62%, 72.22% and 46.48%); for datasets SD1 and SD2 these scores are higher than those found in formation. However, similar to that found in formation, the true positive rate is much lower than that found in with the common location criterion.

7.2 The Real Dataset

Many ships are installed with an Automatic Identification System (AIS). With the use of GPS receivers and other electronic navigation sensors, AIS allows ships to be tracked, providing information about each ship such as its unique identification, course, current position and speed.

A dataset has been obtained that records the movements of ships fitted with AIS within the Solent over a twenty-four hour period; the dataset was provided by Neil Richardson with the use of an AIS receiver. The dataset contains the AIS data from 480 ships. For each individual recording, various information had been recorded including a ship's numerical identifier, its position, its status (e.g., 'underway') and its bearing; each record also had a date and time stamp.

Although there are no known spatial collectives within the dataset, the dataset has been included as an experiment to see how the spatial coherence criteria could be applied to a real dataset. If and when any collectives were identified, a ship enthusiast was contacted who could identify what ships the identifiers referred to and therefore, why they may have been identified as a spatial collective.

7.2.1 Preprocessing

Following an analysis of the ship identifiers (*ids*) that were contained in the dataset, it was noted that spatiotemporal records had been collected for objects other than ships (e.g., the movements of two helicopters had been recorded for a short period of time).

If the coherence criteria are to be applied to a dataset, that dataset must record the positions of each individual entity at regular time steps. Within the ship dataset, some records were found to be missing the necessary information (ship id, position, time); these records had to be discarded and the remaining records used to form dataset RD1. 37 ships had only recorded their position once within the twenty four hour period. After some initial analysis it was clear that some outliers existed within the data; a small group of ships were found to have longitudes and latitudes that represented a location within the South Pacific. Since it was known that the dataset should only contain ships located in the Solent, ships could be removed that had a longitude and latitude outside this area.

RD1 contains the AIS data from 480 ships. The position of each ship was given as longitude and latitudes. Time was recorded in the format of '17:00:00' representing seventeen hundred hours. Some of the data within each record was not needed by the computer program (e.g., status) and was therefore discarded. A ship's id, longitude, latitude, and time stamp were extracted; the position was converted into Cartesian coordinates following the guidance presented by Ordance Survey [2010]; and, the time stamp converted to seconds.

The time steps at which the position of a ship is recorded are mostly distinct between ships. When recording their position, new positions are recorded frequently. However, an examination of the data revealed that some ships only provided data during very short time intervals. The computer program relies on a dataset comprising a series of snapshots where the position of each and every individual is known at each and every time step. Therefore, the data was analysed to try and establish the frequency of the snapshots (timesteps) that would allow the most meaningful snapshots (i.e., where data was known for the most ships); results of this analysis resulted in snapshots at 5 minute intervals. If a ship's position was not known at a given time step, its position was recorded as 'Nan' – this meant the computer program would ignore that ship at that time step. Initially interpolation was going to be performed to allow more positions of ships to be known. Further analysis of the data revealed that when a ship did record its position, it was very frequent (e.g., every few seconds). Once a ship stopped recording it was very rare that that ship would begin recording soon enough to allow interpolation to give an accurate position; often once a ship stopped recording it did not return. Therefore, no interpolation was performed.

7.2.2 Finding the Correct Input Parameters

A ship enthusiast was consulted to help identify the necessary input parameters for each criterion with up to three values being suggested for each. The spatial coherence criteria were applied and the results presented. The ship enthusiast could then observe these results to see what information was being extracted. The results were presented as a series of screenshots, one per criterion, where the members of each spatial collective that had been identified for that criterion were shown in a colour unique to that collective. The user could compare these results to a screenshot which displayed the trajectories of every ship – the trajectory of each ship was shown in a colour unique to that ship; this screenshot is displayed in figure 7.10. To aid the user a representation of the coastline around the Solent has been added to the diagram[1].

It was decided that an initial snapshot constraint of 3 would be set; since the snapshots occurred at 5 minute intervals, this related to a time interval of fifteen minutes if considering consecutive snapshots, or a minimum of three 5 minute intervals if considering intermittent coherence. Similar to that used with the synthetic datasets, a cardinality constraint of 3 was also used. However, values of 4 and 5 were also used for this constraint as an experiment.

Initially the coordinates for every ship were converted to Cartesian coordinates. The user (i.e., the ship enthusiast), found it difficult to relate to these values; window sizes and distances were suggested that were too large – most of the ships within the dataset were found to satisfy the coherence criteria and therefore, too much information had been extracted. As an experiment, to see if it helped the user select more suitable values for the input parameters, the coherence criteria were applied to the original coordinates (i.e., the longitudes and latitudes). The final parameters that were given by the user can be found in table 7.9; please note, that the positions of the ships had not been converted into

[1]The addition of the coastline was obtained from Dr. Jacqueline Christmas

Cartesian coordinates (i.e., were still longitude and latitude), hence the small value for the window of common location (location-based).

The values given by the user seemed to extract a more reasonable level of data – as the results show in section 7.2.3, ports and pilot stations were identified as common locations, and the movement of ships along shipping channels and within ports were highlighted as spatial collectives under the other criteria.

Criterion	**Parameter**	**Value**
Common Location Individual-based	Distance	5000
Common Location Location-based	Window size	0.25
Similar Movement Parameters	Percentage	25%
Formation	Percentage	25%

Table 7.9: The input parameters for the real dataset (RD1) as given by the user (i.e., the ship enthusiast)

7.2.3 Results

Within Chapter 6, results were presented with the use of tables and figures; the tables indicated the number of spatial collectives that had been highlighted for each criterion and the figures visually displayed screenshots from the movies that had been produced. With the dataset that is being considered here, the tables are not really meaningful – it is not known how many spatial collectives, if any, exist within the dataset and therefore, no information exists to compare the results of the table with. Therefore, no tables are shown here. Instead, pictures provide a more meaningful representation of the results.

Common Location

Figure 7.11 shows the results from applying the location-based view of the common location criterion to the RD1; the squares indicate the locations that have been found. It is clear that some of the locations represent ports, namely Southampton, Lymington and

Portsmouth. However, locations were also highlighted that did not correspond to ports. Consultation with the user identified one of these locations as a pilot station; this is an area where each boat must stop at to pick up a pilot if they wish to enter a port. Two additional locations were identified under this criterion that were not ports; the user did not know what they were.

An initial value was specified for the distance in the individual-based common location criterion that could possibly have been considered too large, groups of ships were being highlighted as a possible collective because they were crossing a shipping lane or passing a port. A smaller distance of 5000 units was chosen to see what other information could be obtained. Figure 7.12 displays the entire trajectory of the ships that have been highlighted as occupying a common location for a sufficient number of snapshots, either intermittently or consecutively, with the smaller distance value. Interestingly, many of the groups that have been identified are those that are traveling in or out of a port.

Formation

The formation criterion highlighted some interesting spatial collectives. Figure 7.13 shows the entire trajectory of each ship that was found to be participating in a spatial collective under this criterion; the ships may have only be identified as a collective for subset of this time interval but, the indication of the entire trajectories highlights some interesting information. Areas where these trajectories are located are in the vicinity of ports and shipping lanes. The user stated that this is very plausible. The movements of ships are heavily controlled within ports and it is likely that the ships coming into and out of port are to be highlighted as moving in formation. A similar point can be made regarding shipping lanes. Interestingly more traffic has been identified on the one shipping lane, the westbound lane which carries traffic out of Europe.

Similar Movement Parameters

The similar movement patterns criterion appeared to highlight similar trajectories to those found when applying the formations criterion. The user found it interesting that the majority of collectives that had been highlighted contained ships moving along the shipping lanes. Unlike the formation criterion, a similar amount of traffic was identified on both shipping lanes.

7.3 Discussion

The spatial coherence criteria have been applied to types of dataset, one real and one synthetic, to try to establish whether or not they can be used to efficiently identify the presence of a spatial collective within a dataset. Some discussion has been given on the results, including some statistical analysis, but there are still questions that need to be addressed.

7.3.1 The spatial coherence criteria

The location-based view of the common location criterion did appear to accurately identify the locations where groups of boids had gathered but, since the boids were in constant motion and at a constant speed, minimal meaningful information could be gathered from this criterion. However, when applied to the real dataset, suitable locations were accurately identified with this criterion (i.e., shipping ports and pilot stations).

The individual-based approach of the common location criterion appeared to be very successful in identifying the presence of spatial collectives within the synthetic datasets – when no members of species A were present, no collectives were identified. When applied to the synthetic datasets, the formation and similar movement parameters were found to have much lower accuracy scores and true positive ratings than that found in common location. However, they still obtained high true negative ratings indicating that members of species B were being correctly identified as being from species B most of the time. It could be questioned as to whether both the formation and similar movement parameters criteria are needed. Although they were not found to be as successful as the common location criterion when applied to the synthetic datasets, they have been able to identify the presence of spatial collectives within the dataset. The results of applying the criteria to both the real dataset and the synthetic datasets showed that the collectives identified under the common location criterion were also highlighted by the formation and similar movement parameters criteria; however, these latter two also identified additional collectives within the dataset. The lower accuracy and precision scores could be due to the nature of the dataset: the boids are expected to move at similar speeds to each other and in similar directions; therefore, you would expect lower accuracy and precision scores.

7.3.2 A Human Analyst

The importance of a human analyst was noted in section 4.3 and by other researchers [Andrienko and Andrienko, 2006]. This point has been emphasised in the implementation and application of the coherence criteria.

Each of the criterion require cardinality and snapshot constraints to be defined by the user but also other parameters such as window size and distance for the common location criteria. It would be very difficult, if not impossible, for these values to be hardcoded into the program. The two types of dataset required very different inputs. Often these are not necessarily known to the user prior to using the program and therefore, experiments have to be run to establish what the best parameters are; as was done with the boid data.

The allowance for the user to set these parameters and compare the results of using different values, also allow a human analyst to identify whether all of the necessary data is being captured. This is aided by allowing the analyst to view each result of applying the coherence criteria as a movie which depicts which individuals have been identified as participating in a collective for which criteria. Humans can often see patterns within data very easily [Andrienko et al., 2009]; if the program allows them to see what information is being captured by each criterion, a user may decide that more information could be captured or if too much detail is being recorded, to change the parameters accordingly. This is similar to the approach suggested by Andrienko et al. [2009].

7.3.3 Variable Membership

The way that the computer program has been implemented, two groups may be highlighted as collectives within the dataset but on comparison, one may be the subset of the other – this could occur when the individuals do not occupy coherence over the same series of snapshots.

Figure 7.9 is a graphical representation of the groups that have been identified as participating in a collective within the common location criterion (individual-based view) for a dataset of type SD1. Each row represents a spatial collective that has been identified within the dataset for that snapshot; groups that have satisfied the criterion for an intermittent and consecutive number of snapshots are included within the graph. Within each row, each individual is represented as a unique colour. Although there are 40 boids within the dataset, all but one individual that has been identified as a member of a collective is a member of species A. Subsets of individuals depicted in the bottom row have also been identified as a unique collective (i.e., they are depicted in a different row); this is because the two collectives satisfy the criteria over different snapshots.

A human analyst may identify this as variable membership; however it very much depends on how they interpret the data. For example, an individual may have been considered part of a collective by coincidence, therefore, not indicating variable membership.

7.4 Conclusion

The coherence criteria have been applied to two different types of dataset: a synthetic dataset and a real dataset. The synthetic dataset contained forty boids whose behaviour was controlled through a set of rules: cohesion, alignment and separation [Reynolds, 1987]. To favour the formation of spatial collectives, twenty individuals were given very high parameters for alignment and cohesion; these individuals were referred to as species A. The remaining twenty individuals were given low values for these parameters to disfavour the formation of collectives. Three datasets were produced, two of which had two species present; however, within one, species A had a maximum value of 1.0 for both alignment and cohesion. A third dataset contained forty individuals of species B. It was thought that the spatial coherence criteria should identify more spatial collectives where there are two species present. In addition to the synthetic datasets, a real dataset was obtained that contained the movement of ships fitted with AIS equipment within the Solent during a twenty four hour period. With the aid of ship enthusiast, who played the role of the human analyst, the set of spatial coherence criteria were also applied to this dataset.

The results that have been presented in this Chapter are positive. The statistical analysis for the synthetic dataset found reasonably high precision rates and very high recall rates for each of the coherence criterion when they were applied to the synthetic dataset.

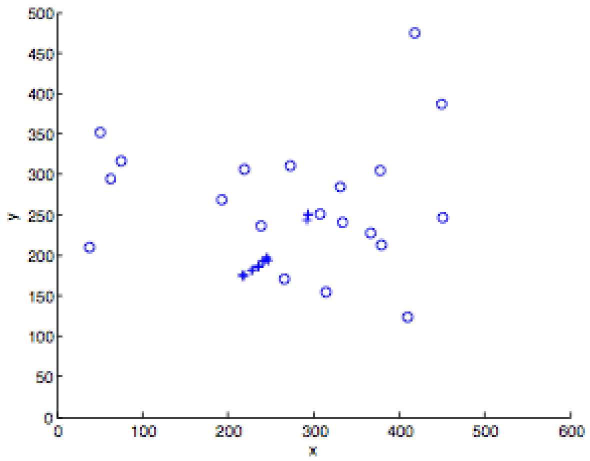
Although the location-based view of the common location criterion could not be fully evaluated for the synthetic dataset, this criterion revealed meaningful locations when applied to the real dataset (i.e., ports and pilot stations). For the synthetic dataset, a comparison of the criteria indicated that the individual-based approach of the common location criterion had the best performance scores and could successfully identify species A from B. The formation and similar movement parameters criteria also performed well but not to the same degree as common-location (individual-based). It was noted that this could be due to the behaviour of the boids; although parameters were set to try and favour the formation of collectives in only one species, each boid moved at the same speed and in a similar way.

Application of the coherence criteria to the real dataset led to positive feedback from the analyst. Spatial collectives had been identified that were meaningful to the user: ports, pilot stations and shipping lanes. Ideally, the coherence criteria would have been applied to Cartesian coordinates; however, since the space that was being considered (i.e., the Solent), is so small, it was difficult for the user to relate to these values. Therefore, the criteria were applied to the longitude and latitude values for each ship.

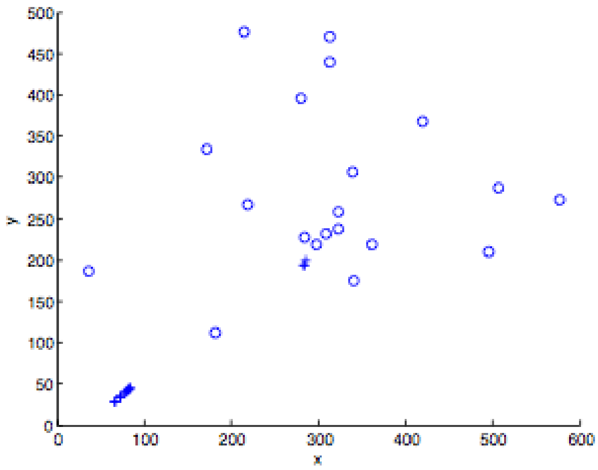
Although the results are positive, the current implementation of the coherence criteria is not complete. Chapter 5 had suggested many ways in which the criteria could be expanded. Each criterion was implemented in its most simplest form to establish if the method could identify the presence of spatial coherence criteria within a dataset. The results presented in this Chapter indicate that, even in their simplest form, they can with a good degree of accuracy and precision. Further work may improve on these scores if every aspect of each criterion was implemented (Chapter 5). The coherence criteria only allow the presence of a spatial collective to be highlighted, nothing can be said about the types of the collectives that are being detected. However, extensions to the criteria are also likely to allow the different types of spatial collective to be distinguished according to how they satisfy a particular criterion.

The current implementation would also need to be extended for real data, which is likely to contain some error, especially if the information is obtained via GPS tracking technologies. Percentages have been used to compare values for parameters such as speed and location but no further consideration has been taken of the error introduced due to GPS. In spite of this, the information that has been obtained from applying the coherence criteria to dataset RD1 is still meaningful to a user (i.e., a ship enthusiast). However, if the coherence criteria were to be applied to a larger dataset, the error introduced by GPS would have to be considered.

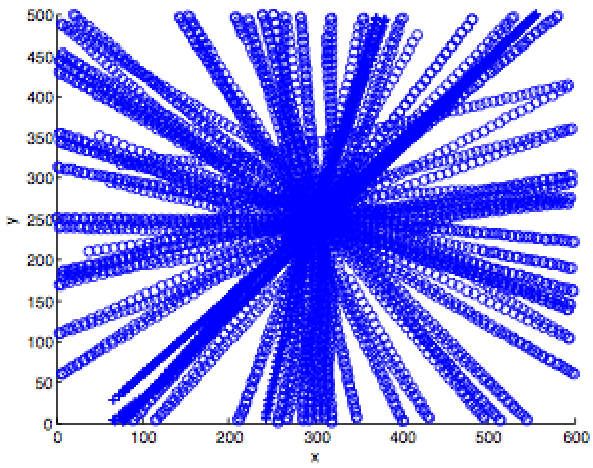
In addition to the extension of the coherence criteria, there are many other ways in which the proposed method could be extended. Currently, the identities of the locations found to satisfy the common location criteria (location-based) criterion are not retained. If the computer program could track these identities, more information could be obtained about the collective and, therefore, a deeper analysis provided (e.g., does a spatial collective always visit the same location?); this information may also help identify the type of spatial collective that is being observed. Instead of a human analyst needing to input the necessary parameters in order for the coherence criteria to be successfully applied, it is possible that machine learning techniques could be used to help find the optimum values for these parameters. The results of applying the coherence criteria to the two types of dataset could be compared to natural language versions: a set of users could be asked to describe what they are observing and compare the natural language terms that they use to what has been detected. These experiments could identify whether the coherence criteria reflect the terms we use in everyday language but also if there is a form of spatial coherence that has been omitted within the proposed method. Although such experiments would be very interesting, they are outside the scope of this thesis. Chapter 9 discusses some of the possible extensions to this work in more detail.



(a) Snapshot 200

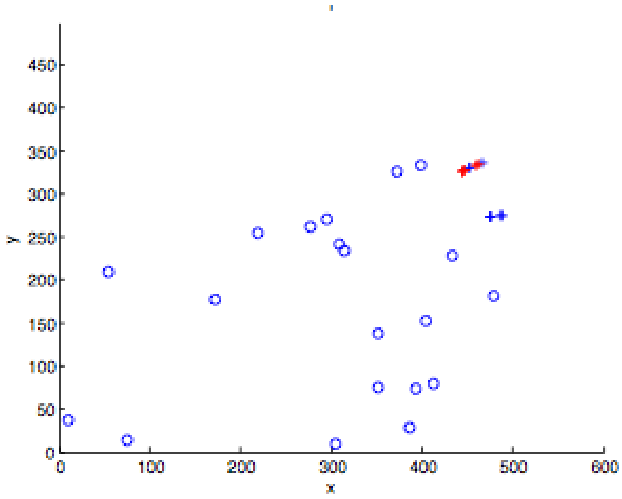


(b) Snapshot 400

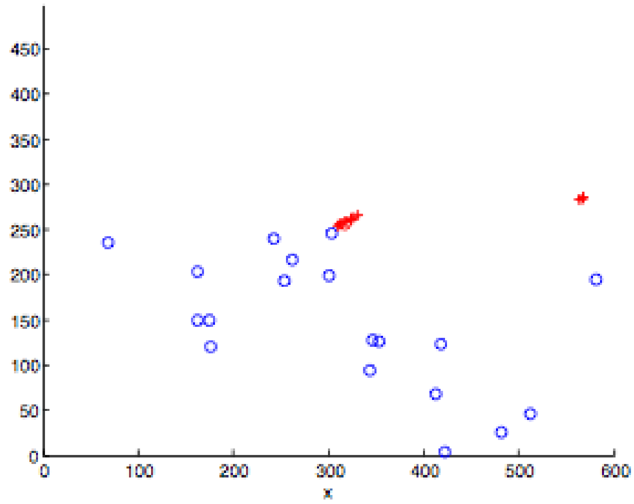


(c) Trajectories between Snapshots 200 and 400

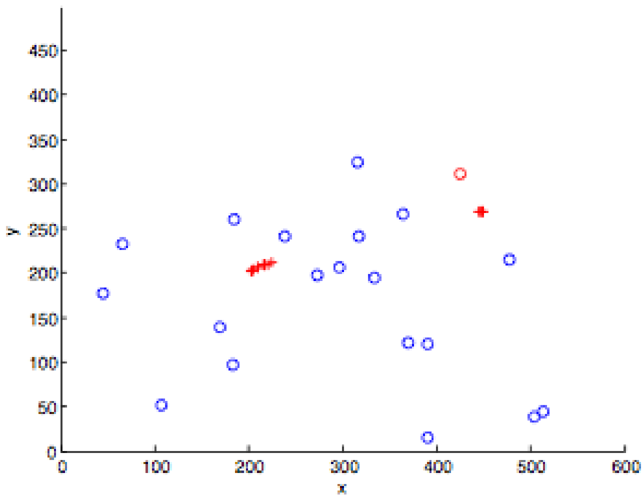
Figure 7.1: Examples of the snapshots that are produced before the coherence criteria are applied. The first two snapshots shows the position of all forty boids at that snapshot; members of species A and B are denoted by '+' and 'o' respectively. The final screenshot shows the trajectories off the forty boids between the two depicted snapshots (i.e., 200 and 400).



(a) Snapshot 1

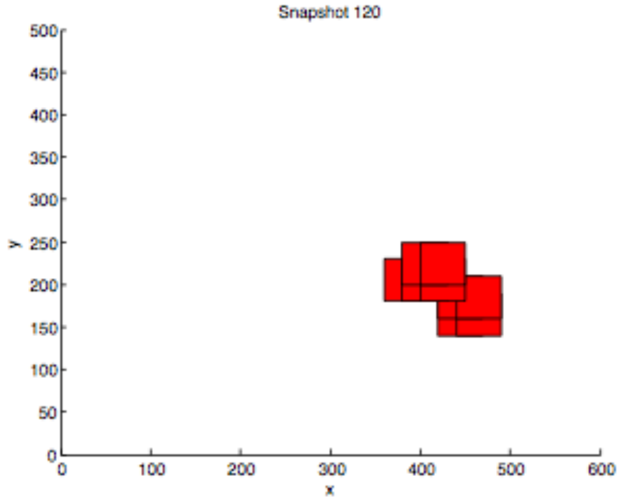


(b) Snapshot 20

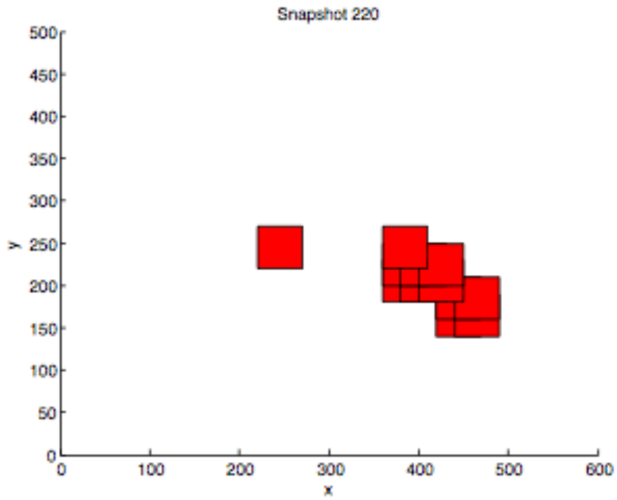


(c) Snapshot 35

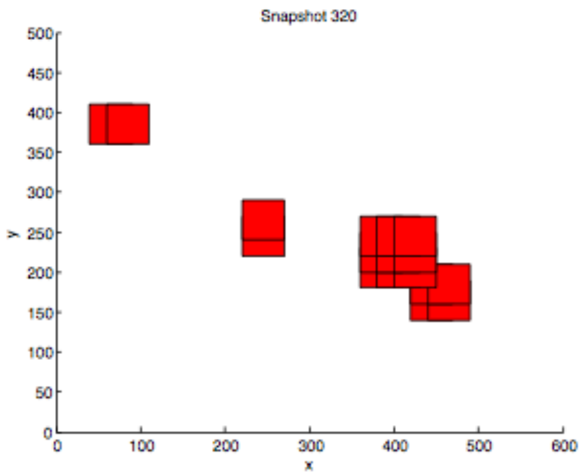
Figure 7.2: Examples of the screenshots produced for common location criterion (individual-based) with individuals identified as satisfying the criteria are coloured red. Each snapshot shows the position of all forty boids at that time. Members of species A and B are denoted by '+' and 'o' respectively.



(a) Snapshot 120

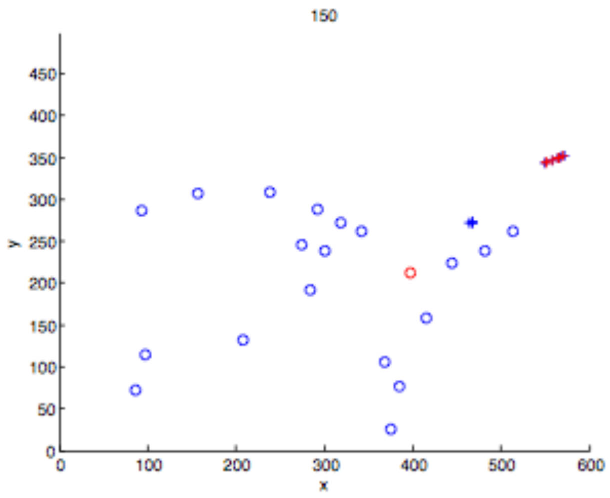


(b) Snapshot 220

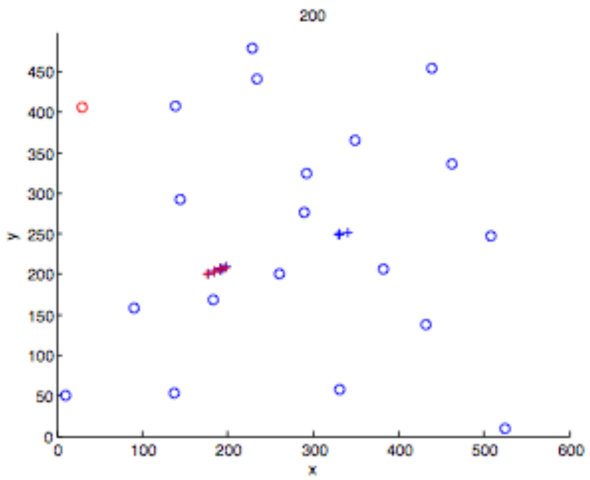


(c) Snapshot 320

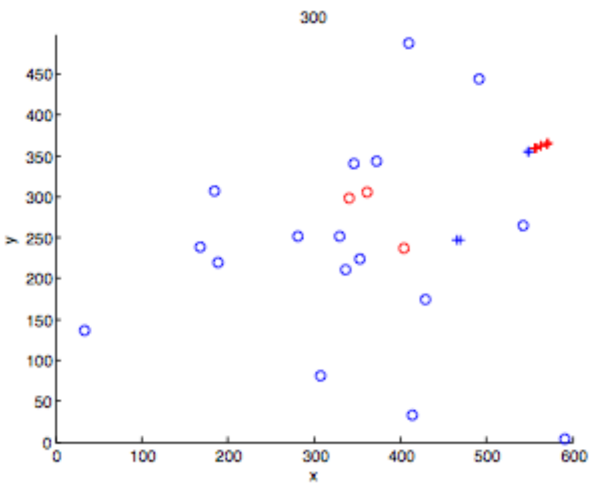
Figure 7.3: Examples of the screenshots produced for common location criterion (location-based) where the locations that have been identified as satisfying the criteria are coloured red.



(a) Snapshot 150

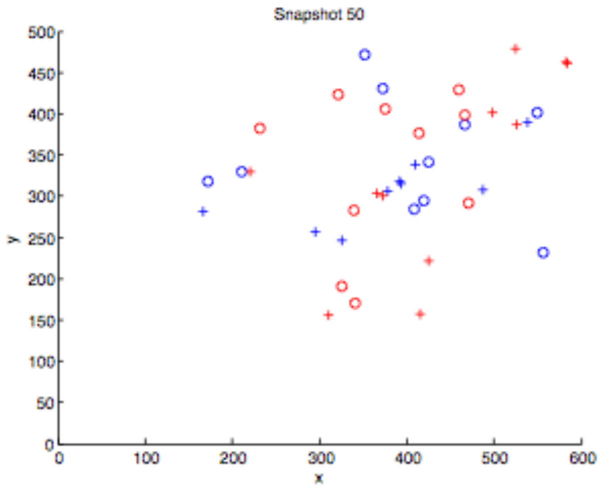


(b) Snapshot 200

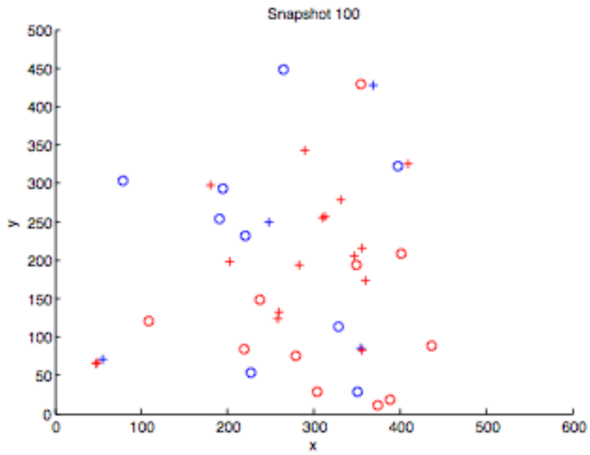


(c) Snapshot 300

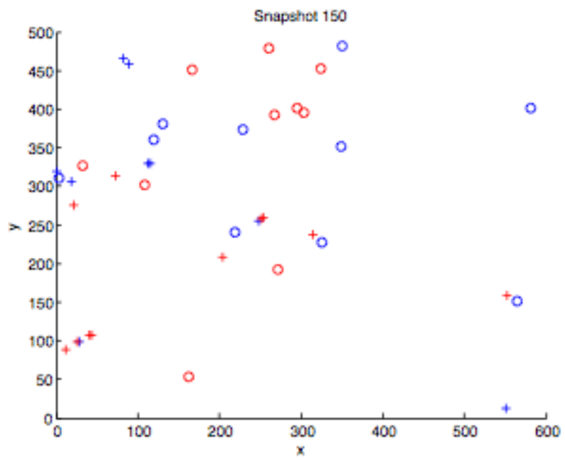
Figure 7.4: Examples of the screenshots produced for formation criterion with individuals identified as satisfying the criteria are coloured red. Each snapshot shows the position of all forty boids at that time. Members of species A and B are denoted by '+' and 'o' respectively.



(a) Snapshot 50



(b) Snapshot 100



(c) Snapshot 150

Figure 7.5: Examples of the screenshots similar movement parameters criterion with individuals identified as satisfying the criteria are coloured red. Each snapshot shows the position of all forty boids at that time. Members of species A and B are denoted by '+' and 'o' respectively.

		Identified	
		A	**B**
Actual	**A**	99.25%	0.75%
	B	25%	75%

(a) SD1

		Identified	
		A	**B**
Actual	**A**	94.83%	5.1665%
	B	18.92%	81.08%

(b) SD2

		Identified	
		A	**B**
Actual	**A**	0%	100%
	B	0%	100%

(c) SD3

Figure 7.6: Confusion matrices for common location (individual-based)

		Identified	
		A	**B**
Actual	**A**	93.17%	6.83%
	B	45.83%	54.17%

(a) SD1

		Identified	
		A	**B**
Actual	**A**	91.17%	8.83%
	B	43.33%	56.67%

(b) SD2

		Identified	
		A	**B**
Actual	**A**	73.08%	26.92%
	B	70.33%	29.67%

(c) SD3

Figure 7.7: Confusion matrices for Formation

		Identified	
		A	**B**
Actual	**A**	98.58%	1.42%
	B	45.08%	54.92%

(a) SD1

		Identified	
		A	**B**
Actual	**A**	96.17%	3.83%
	B	37%	63%

(b) SD2

		Identified	
		A	**B**
Actual	**A**	71.67%	27.83%
	B	82.08%	17.92%

(c) SD3

Figure 7.8: Confusion matrices for Similar Movement Parameters

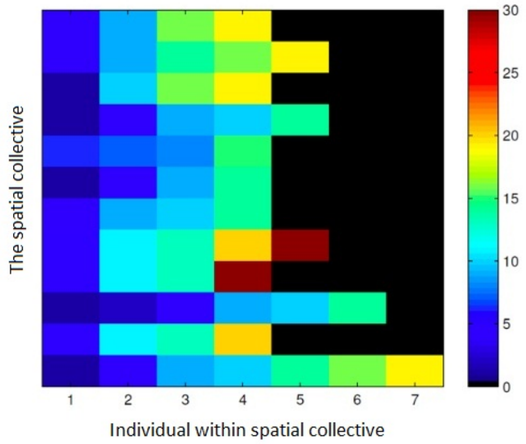


Figure 7.9: An example of the groups identified as a collective within a dataset. Each row represents a spatial collective that has been identified within the dataset for that snapshot with each individual uniquely coloured.

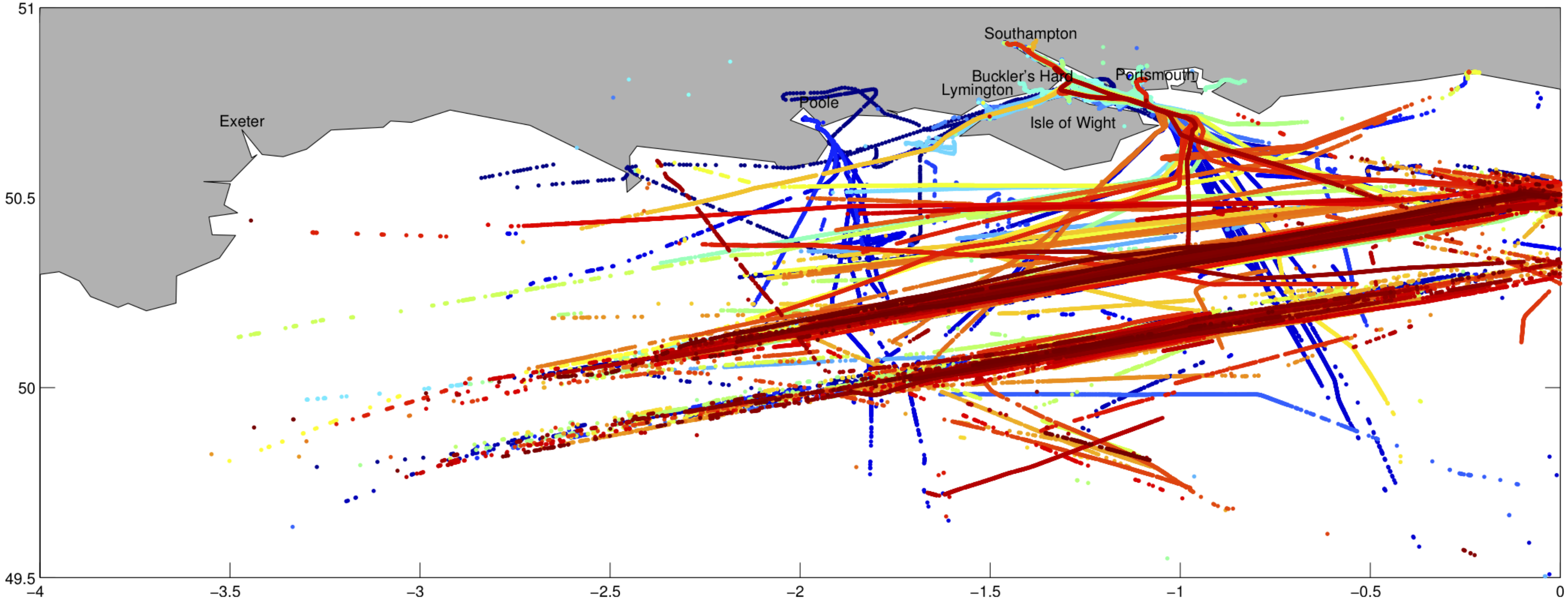


Figure 7.10: The movements of ships within the Solent.

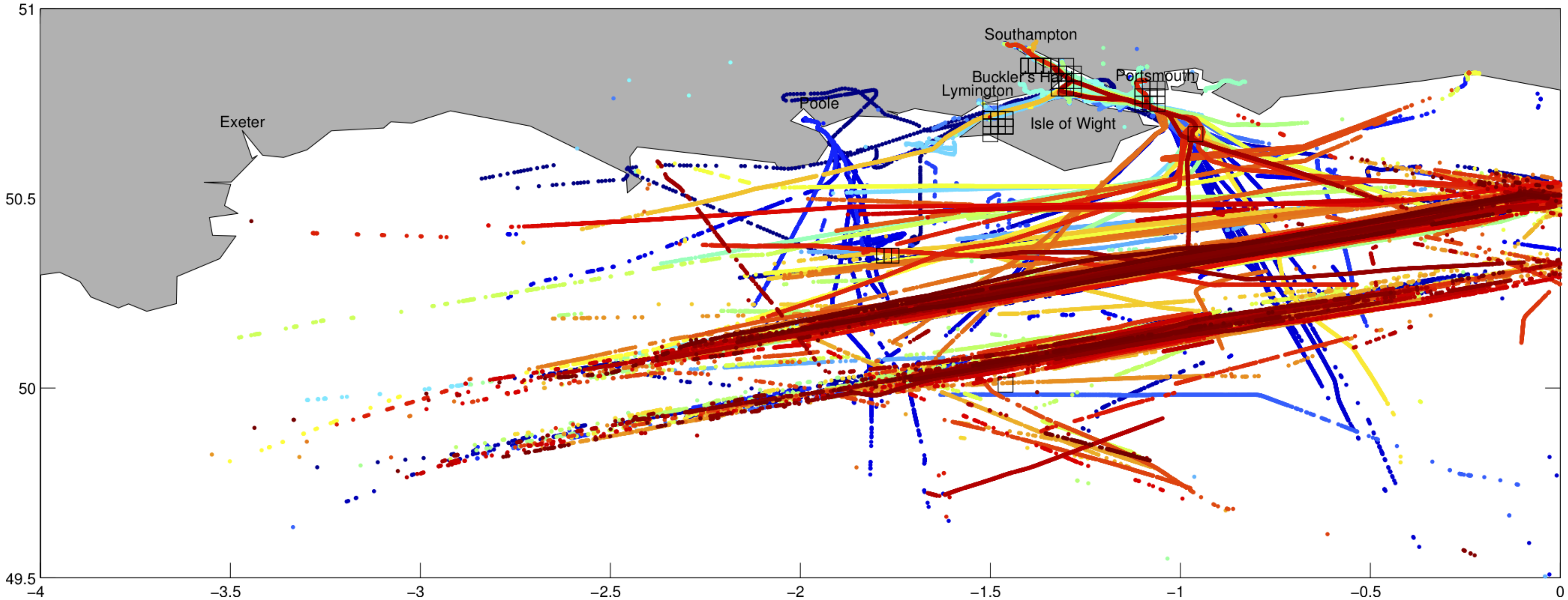


Figure 7.11: The Common Locations Identified (location-based)

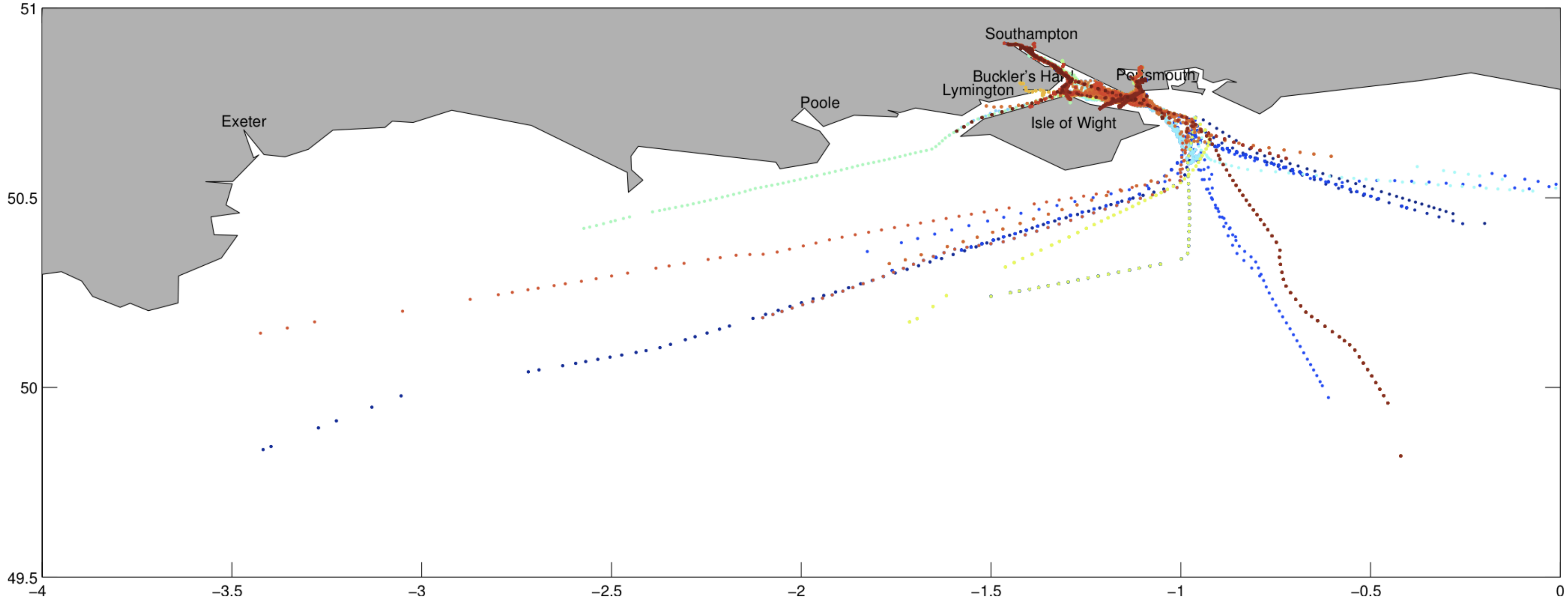


Figure 7.12: The ships identified under the common locations criterion (individual-based).

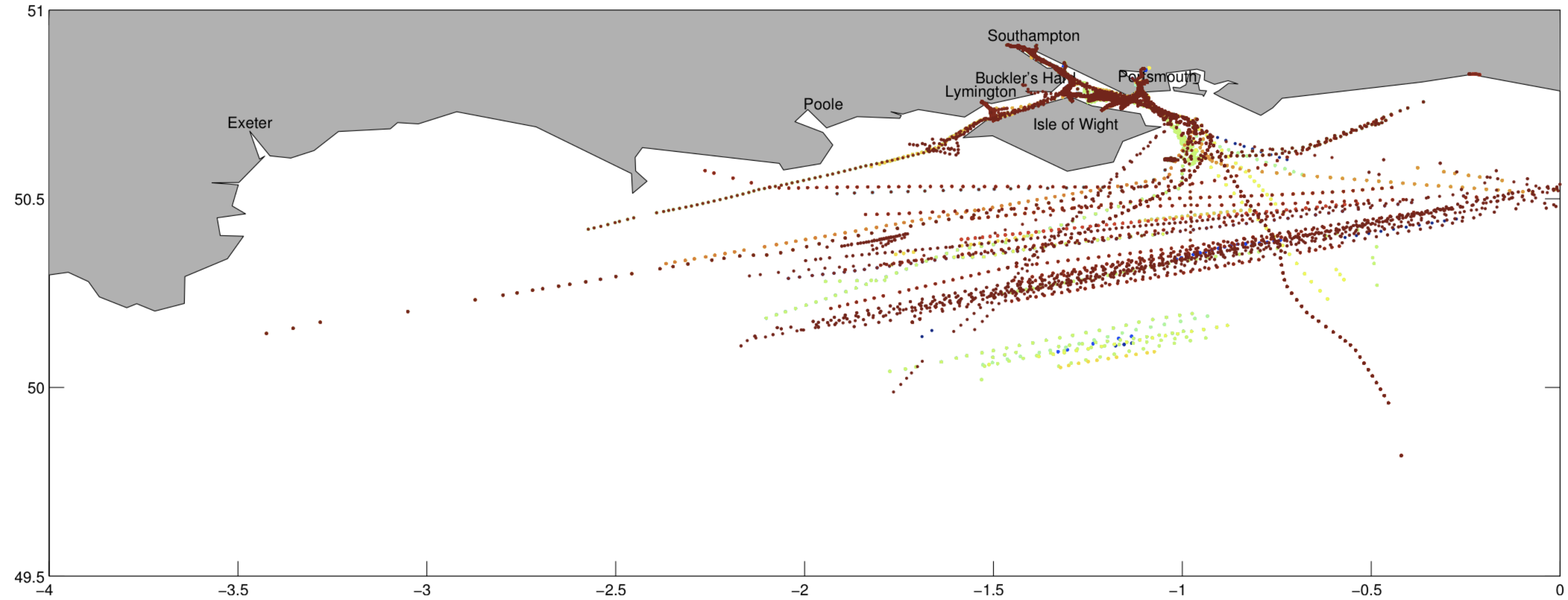


Figure 7.13: The ships identified under the formation criterion.

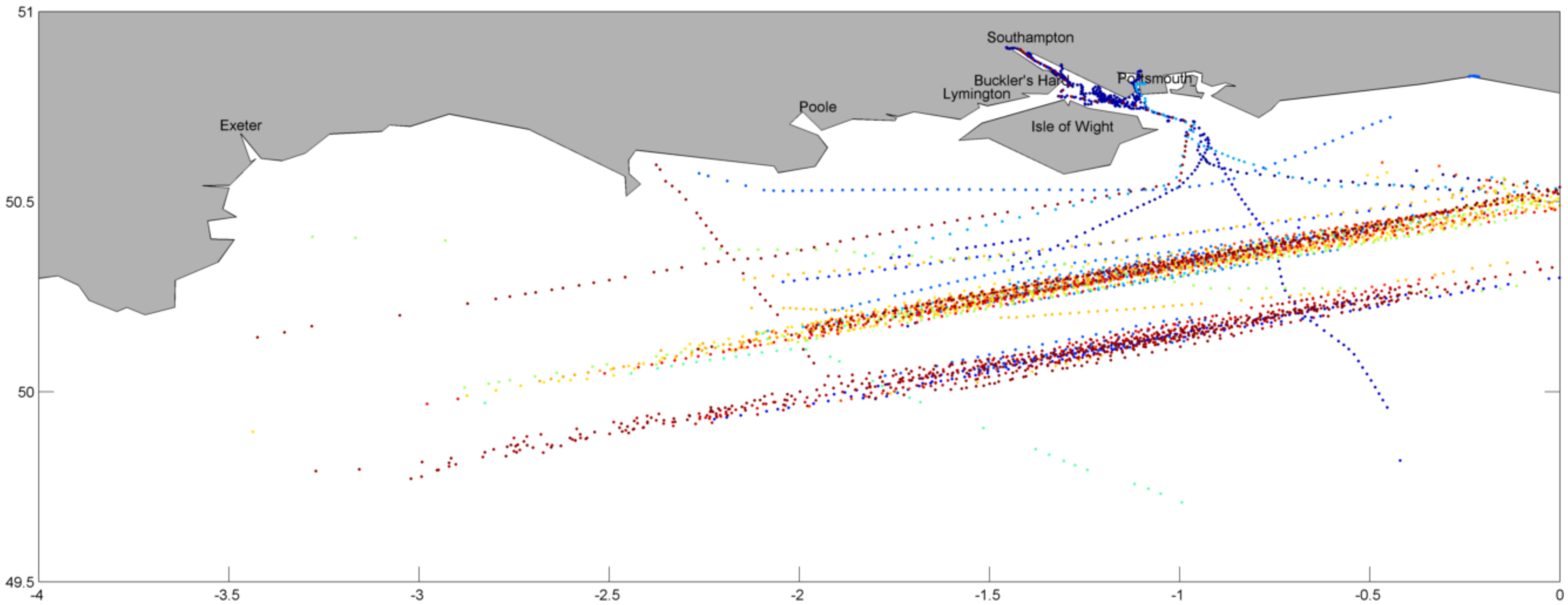


Figure 7.14: The ships identified under the similar movement parameters criterion.

8 Towards a Taxonomy of Spatial Collectives

A method has been presented that identifies the presence of spatial collectives within a dataset (Chapter 5). However, only the presence of a collective is highlighted, no attempt has been made to identify that collective's type. The combination of spatial coherence criteria that have been satisfied could give some indication of this but no further discussion has been given on the different types of spatial collective that may exist.

The general taxonomy outlined in Chapter 3 could be applied to the spatial collectives extracted from a movement dataset; however, the user may not have all of the necessary information to classify the collective. For example, an orchestra during a performance could be classified as a collective consisting of a constant set of individuals (M1, D1); who follow a partitioned role structure (R2.2); whose locations along with that of the collective is fixed (L2.1.1); and, whose source of coherence is an internal collective purpose (C2.2.2). The only information known about a spatial collective is what is contained within the dataset from which it has been extracted; it is assumed that the dataset records only the positions of the individual members at given time steps throughout a given observation period. Consider the example of the orchestra. A dataset could record the positions of each and every musician at regular time steps throughout the performance; an analysis of this data could reveal a group of stationary individuals but it is unlikely that a user could identify that they are all in the same location due to a collective purpose. It also may not be clear that the users are following a partitioned role structure, especially, if only examining the movement patterns of the orchestra during a single performance. If observed over a reasonably long period of time it may become apparent that the same individuals within the collective always sit in similar groups and, therefore, suggest that they are following a partitioned role structure, but this relies on the observation period being long enough to observe the pattern and the user to make this assumption.

Spatial collectives could be considered a small subset of those identified in the previous taxonomy. The existing criteria need to be examined to assess the extent to which they can distinguish between the different types of spatial collective; some are irrelevant and can be omitted but some could be extended. Therefore, this Chapter presents a suggested taxonomy of spatial collectives. Due to a lack of available datasets, the taxonomy cannot be fully evaluated or completed; however, it does indicate possible extensions to the work presented here.

Recent research into collective motion has lead to the development of the Three-Level-Analysis (TLA) framework [Wood and Galton, 2009a, 2010a,b]; this framework indicates additional criteria that should be included in the taxonomy that are specific to movement pattern analysis involving collectives. A summary of the TLA framework is given in section 8.1 followed by the criteria that form the basis of the new taxonomy (section 8.2). Section 8.3 suggests how the taxonomy could be extended to include distinctions based of the movement behaviour that is exhibited by the collective. The Chapter concludes with a discussion on any dependencies that have been introduced (8.4.1), along with other concepts that may need to be addressed (8.4).

8.1 The Three-Level-Analysis (TLA) Framework

Research undertaken to establish the different types of motion that can be exhibited by collectives resulted in the proposal of the TLA framework (Wood and Galton [2009a, 2010a,b]). The framework analyses and represents collective motion by taking into account the importance of granularity in both the way collectives and motion are described. The former is considered by independently examining three aspects of collective motion and extracting the relevant movement pattern(s) from each: the motion of the collective when considered as a single entity, the evolution of the collective's footprint and the motions exhibited by the individual members. These three levels can be considered as three separate levels of spatial granularity. To account for the importance of granularity in the way motion is described, the TLA framework includes a set of *episodes*.

Within the framework, the three levels have been chosen since they each represent an important aspect of the collective. A collective can be viewed on two levels: at a high-level where the collective can be considered as a single entity and at a low-level where a group of individuals are observed. Although the motion of the collective arises from the motions of the individual members, it is not sufficient to solely consider the aggregated motions of the individuals. As already noted in section 3.2.2, the two motions may be qualitatively distinct and important information could be lost if only one level of the collective is examined. The motion of the collective, when considered as a single unit, could be extracted by choosing a representative point (e.g., the centroid of a collective). However, examining only this motion, does not allow for all possible aspects of collective motion to be analysed. Between the two levels, it may be possible to analyse the collective as occupying a two- or three-dimensional region of space. This region could be represented by a footprint; the way in which it evolves could allow more distinct classes of collective to be found. For example, the ability to split and merge are two important properties of some collectives (e.g., a flock of birds). If the motion of the collective is only observed as a point, this information would not be available and, therefore, not allow this type of collective to be represented.

The way in which motion is described is dependent on the granularity at which it is observed, especially temporal granularity [Wood and Galton, 2010b]. For example, at a high-level of granularity running can be seen as the movement from one place to another; at a low-level of granularity it can be observed as the repeated movement of one leg after another. If the movement patterns of collectives are to be sufficiently analysed it should be possible to consider the patterns at multiple levels of granularity; different features that indicate the type of collective being observed may become apparent at different levels of granularity. To account for this, the TLA framework incorporates the use of *episodes* where an episode is defined as 'a maximal chunk of homogeneous process at a given level of granularity' [Wood and Galton, 2010a]. Homogeneity will depend on the level of granularity that has been adopted; thus an episode which describes a particular movement pattern at one level (e.g., a person walking from A to B), may at a fine level of granularity be seen as a set of episodes (e.g., the movement of one leg after another). The use of episodes can be seen as similar to that used by Mountain and Raper [2001a,b] and Dykes and Mountain [2003], but also to the use of primitives by Dodge et al. [2008] and Andrienko and Andrienko [2007b]. Unlike the use of primitives, the TLA framework allows movement patterns to be observed at multiple levels of granularity. A predefined list of episode types for each of the three aspects of collective motion are included within the framework; some of which are detailed in Wood and Galton [2010b] and further discussion can be found in Chapter 9.

8.2 The Criteria

The new taxonomy must be able to distinguish between the prominent features of spatial collectives. The groups of individuals that the taxonomy will be applied to have already been found to exhibit at least one feature of collectivity (i.e., common location, similar movement parameters or formation). This information can be used as a way of distinguishing the different types of spatial collective and therefore, should be included in the taxonomy.

Given that collectives could also be classified according to the movement patterns that they exhibit, the TLA framework highlights important aspects of collective motion that should be considered in the new taxonomy. The three aspects of collective motion that have been identified are fundamental features of collectives and, if the type of spatial collective is to be identified, the ways in which each of these features vary should be considered. The different episode types that have been defined at each of the three levels may also allow collectives to be classified in more detail. Based on these concepts, the following criteria have been identified as forming the basis of the new taxonomy:

- membership,
- location,
- formation,
- common location,
- depth.

There are two clear omissions to this list: coherence and role. The term coherence was originally used to refer to the source of the coherent behaviour. Coherent behaviour could have arisen through spatial actions but also exhibited through the interactions and intercommunications between the individual members. The groups that have been highlighted as spatial collectives, using the approach outlined in Chapter 5, are those that satisfy at least one of the predefined spatial coherence criteria (i.e., they exhibit a form of spatial coherence over a series of snapshots). A coherence criterion could be satisfied through individual members sharing: a common location, similar movement parameters or formation; intercommunications and interactions are not really considered and may not be available in the dataset. Within the new taxonomy, a criterion could be included which formally represents the way in which a group has been identified as a possible spatial collective (i.e., the type of spatial coherence that it exhibits). However, this is already covered by the other criteria, namely the location, common location and formation criteria.

The role criterion had been included in the general taxonomy to classify collectives according to the ways in which the individual members of a collective could be differentiated by the role that they played. Three types of role structure were enumerated: hierarchical, partitioned and individualistic. Roles were played by individuals; for example, the members of a committee could fulfil roles such as treasurer, secretary and chairperson. When analysing movement patterns alone it may be difficult to identify this information. Although it may be possible to identify a single leader [Dodge et al., 2008], it is unlikely a group could be singled out as leaders (i.e., a hierarchical model). It is also seems unlikely that an individualistic role structure could be distinguished from a spatial collective whose members are not differentiated by role. Sub-collectives could be identified within a dataset but, within a movement dataset, these are more likely to be considered to be collectives of collectives; as noted in Chapter 3, this is not the same as a partitioned collective.

Referred to as 'behavioural patterns', Dodge et al. [2008] have identified some patterns that could suggest certain roles being played: *leadership*, *pursuit/evasion*, *parental protection* and *courtship*. One approach is to include a role criterion which enumerates the different possible 'behavioural patterns'. It is questionable whether this approach would allow more distinct classes to be represented within the taxonomy or allow prominent features of spatial collectives to be classified. Patterns such as *courtship*, *pursuit/evasion* and *parental protection* are only exhibited by a small number of spatial collectives. Since only minimal role pattern models can be identified using movement patterns alone, the role criterion has not been included in the new taxonomy.

The remainder of this section will detail these criteria along with an explanation of how they differ from the way they were set out in the general taxonomy of collectives.

8.2.1 Membership

In the existing taxonomy, the membership criterion made an initial distinction between collectives that always have constant membership and those that can have variable membership. Those collectives that were defined as having variable memberhsip, were further distinguished according to whether or not the collective required the same number of members to survive (i.e., *constant cardinality*) or if they could have a variable number of members (*variable cardinality*). Constant cardinality was split into two categories: *robust constant cardinality* and *weak constant cardinality*. This distinction was included to distinguish between those collectives that must have a certain number of members to exist in order to exist (i.e., robust) and those that should have a certain number of members but, should one be lost, the collective would continue to exist but be considered damaged or incomplete (i.e., weak). If classified as having variable cardinality, collectives could be classified according to the minimum number of members required for the collective to exist: one or two.

The approach proposed in Chapter 5, identifies a group of individuals as a spatial collective if they have enough members that satisfy at least one of the spatial coherence criteria for the necessary number of snapshots. If it is always the same members, the group could be said to exhibit *constant membership*, otherwise *variable membership*.

The method relies on the user specifying a cardinality constraint before the coherence criteria are applied which corresponds to the minimum number of members that a collective must have in order to continue to exist. Collectives considered as having variable membership could be further classified according to the cardinality of those members – must they always have the same number of members (i.e., *constant cardinality*) or, could the number of members vary (*variable cardinality*)? This could be specified as an additional constraint specified by the user before the coherence criteria are applied. Unlike the previous taxonomy, it seems unlikely that enough information is available within the data to distinguish between robust and weak constant cardinality. How can a collective be considered damaged if its function is not necessarily known?

```
[M1] Constant membership.
[M2] Variable membership.
    [M2.1] Robust constant cardinality.
    [M2.2] Weak constant cardinality.
    [M2.3] Variable cardinality.
```

8.2.2 Location

The previous taxonomy analysed the location of each collective, the locations of its individual members and the relationship that existed between the two. Assuming individuals are point-like, their locations were given by their Cartesian coordinates. Where the individual members were too widely distributed throughout space, the collective was not considered to have a location. If a collective could be assigned a location, that location was represented by a footprint that had been obtained according to a pre-defined procedure. These collectives (i.e., those that could be assigned a location), were split into those whose location was *fixed* and those whose location was *variable*. The motion of a collective was considered as the motion of a representative point (e.g., the collective's centroid). If the point did not move, taking into consideration GPS error, from one snapshot to the next it would be considered fixed, otherwise it would be considered to have a variable location. Regardless of whether the collective could be assigned a location, each collective was examined to see whether their members were fixed or variable.

A collective whose motion was variable along with the motions of its individual members, was analysed to see if the two motions were correlated or uncorrelated. Three cases of correlation were enumerated each relating to the relative positions of the individual members (i.e., their *formation*): *none*, *constant* or *canonical*. If a collective's motion was classified as being uncorrelated with the motions of its individual members, the individual members could all be exhibiting qualitatively similar or different motions. If the individuals were all exhibiting motion that was qualitatively the same, the formation of the individuals were considered (i.e., none, constant or canonical).

Many of these distinctions can still be made when given movement data as the sole input and therefore, could distinguish between prominent features of spatial collectives, but some could be removed. The method proposed in Chapter 5 could identify a spatial collective that cannot be considered to have a location. The common location criterion can identify collectives who regularly come together to meet (e.g., a choir, a reading club); these spatial collectives are unlikely to be assigned a location when they were not meeting. As noted in Chapter 5, these types of collective are subject to temporal scope – if a group of individuals only meet once during the observation period they may not be highlighted as a spatial collective. A group may be found to have similar movement parameters but be too distributed to be associated with a location.

Using the approach proposed in Chapter 5, two groups may be highlighted as spatial collectives but, on comparison, one may be the subset of the other (i.e., a sub-collective of the original collective); it is possible that these types of collectives could be themselves members of another spatial collective. This may occur when the individuals do not exhibit spatial coherence (i.e., satisfy the coherence criteria) over the same series of snapshots. For example, individual sections of a choir (i.e., sopranos, altos, tenors or basses), or an orchestra, may come together to rehearse their own individual parts. Referred to as sectionals, these rehearsals often occur when preparing for a performance – the participants of these rehearsals could be considered sub-collectives of the original spatial collective, the orchestra.

Under the general taxonomy of collectives, an orchestra or choir would have been referred to as a partitioned collective; the different sections (referred to as sub-collectives) could be differentiated according to the roles played by the individual members. However, information regarding role is not present within the data, the movement parameters that are a consequence of those roles are. Further research may be able to identify roles from movement patterns but this is not considered here. Although an individual's movement patterns may be a result of the roles that they play, this cannot be taken as fact. For example, consider a University cohort. Observing only the individual students' movement patterns, the individuals would exhibit the same type of behaviour as that of the orchestra when they split to go to their different lectures. Their movement patterns are not really a result of the roles that they play – just timetabling.

Application of this taxonomy to real data may discover that this level of detail cannot be identified from the dataset. However, it has been included in the taxonomy since it appears to distinguish between very different types of spatial collectives.

```
[L1] Collective cannot be assigned a location.
    [L1.1] Members cannot be assigned a location.
    [L1.2] At least some members can be assigned a location.
[L2] Collective has a location.
    [L2.1] Location of collective is fixed.
        [L2.1.1] Location of members is fixed.
        [L2.1.2] Location of members is variable.
    [L2.2]] Location of collective is variable.
        [L2.2.1] Location of members is fixed.
        [L2.2.2] Location of members is variable.
            [L2.2.2.1] Motion of individuals and collective is
                       correlated.
            [L2.2.2.2] Motion of individuals and collective is not
                       correlated.
```

Taking these points into consideration, the new taxonomy will initially distinguish between those spatial collectives that can be assigned a location and those that cannot. If a collective cannot be assigned a location, it will be analysed to see if its members can. Taking into account GPS error, if a spatial collective can be assigned a location, it will be examined to see if their locations are fixed or variable. Amongst the collectives which have variable locations, and whose individual members have variable locations will be those where the two motions are correlated and those where they are not.

8.2.3 Formation

The location criterion in the general taxonomy (Chapter 3), classified collectives according to the relationship between the motions of the individual members by looking at their *formation* (i.e., whether or not the relative positions of the individual members were maintained). The inclusion of this information reflected one of the three levels that had been identified in the Three-Level-Analysis (TLA) framework (section 8.1) but has not been included within the location criterion in the taxonomy of spatial collectives.

On reflection, it seems inappropriate that this information should be included with the location criterion: the two features of collectives are not necessarily dependent on the other. For example, the general taxonomy only allows the formation of the members to be considered if the locations of both the collective and its individual members are variable. However, consider an example of uncorrelated motion: the dancers around the maypole.

The collective is essentially fixed whilst the individual dancers move around the maypole. If classifying the collective based on location alone, under the existing taxonomy, this collective would be considered as type L2.1.2; the taxonomy did not offer any further opportunity to comment on the relationship that existed between the positions of the individual members for this type of collective.

One could simply replicate the distinctions required relating to formation within L2.1.2; however, this approach could be considered inefficient and unwieldy. It also does not recognise the important role that the relationship between the individual members could play in distinguishing a spatial collective with respect to its motion – section 8.3. Therefore, an additional criteria has been included within the new taxonomy which classifies a spatial collective according to the relationship between the individual members of the collective; this criterion contains a revised version of the information previously held within the location criterion. An initial distinction is made between those collectives whose individuals exhibit qualitatively similar motion and those that do not. Of those collectives whose individual motions are qualitatively similar, the relationship between those individuals is examined by considering their relative positions. Individuals participate in a *constant* formation if they always maintain their relative positions and *canonical* formation if they only intermittently maintain their relative positions. If individuals never appear to maintain their relative positions, they are considered to have *no* formation.

```
[F1] The individuals' motions are not qualitatively the same.
[F1] The individuals' motions are qualitatively the same.
    [F2.1] No formation
    [F2.2] Constant formation.
    [F2.3] Canonical formation.
```

It should be noted that this criterion takes into account one of the ways in which a group of individuals could have satisfied one of the spatial coherence criteria and therefore, been identified as a spatial collective – the formation criterion.

8.2.4 Common Location

One of the ways in which a group may have been highlighted as a spatial collective is due to their sharing a common location. This information is not included within the location criterion that has been discussed in section 8.2.2 – the location criterion focuses on whether or not a spatial collective's location changes and if so, how this relates to the evolution of the members' locations; it does not look at the identity of the location occupied (i.e., whether or not the location is always the same).

A spatial collective could have satisfied this coherence criterion in one of four ways:

- the individuals could always share the same common location during a period of observation (e.g., the trees within a forest);
- the individuals could always share a common location but the location varies during a period of observation (e.g., a platoon on the march);

- the individuals do not always share a common location but do come together on more than one occasion to share a common location - when they come together, the common location is always the same (e.g., a University cohort which regularly meets on the University campus);

- the individuals do not always share a common location but do come together on more than one occasion to share a common location - when they come together, the common location varies (e.g., the members of a local reading group – the members often take turns in hosting a session, they do not always share a common location but, when they do, the location varies according to which member of the group is hosting the session).

With regards to the new taxonomy, this information will be included within an additional criterion, common location criterion. Some spatial collectives may not have satisfied this criterion (i.e., never share a common location); therefore, an initial distinction is made between whether the spatial collectives never share a common location and those that do (either continuously or intermittently). If found to share a common location, the spatial collective can be classified further according to whether or not the common location is the same (i.e., *constant common location*) or changes (i.e., *variable common location*).

The inclusion of the common location criterion within the updated taxonomy is one way in which spatial collectives who regularly come together may be discriminated. However, the way in which a collective is classified under this criterion is clearly subject to the granularity that its movement is observed at, both spatially and temporally (section 5.3.1). The method used in identifying common locations in Chapter 5 (i.e., the use of grid squares) could be adopted but, again this relies on a suitable size of grid square being chosen. It may be possible to begin with a larger grid square and then reduce the grid square gradually. However, this may depend on the application and must be specified by the user. A more detailed discussion of this issue can be found in Chapter 9. There are clear links between this criterion and the location criterion – see section 8.4 for further discussion on these dependencies.

```
[CL1] Individuals never share a common location.
[CL2] Individual members always share a same common location.
    [CL2.1] Constant common location.
    [CL2.2] Variable common location.
[CL3] Individual members intermittently share a common location.
    [CL3.1] Constant common location.
    [CL3.2] Variable common location.
```

8.2.5 Depth

The depth criterion ultimately identified whether none, some, or all members of a collective were themselves collectives. This could be an important distinction between the different types of spatial collective. Although it may not always be possible to obtain this information from the data (e.g., if the observation period is too short or sampling rate too infrequent); it is possible, in theory, that the approach proposed in Chapter 5 may identify spatial collectives that are members of another spatial collective.

The way in which a spatial collective is classified under this criterion, will depend on the spatial granularity that the data is analysed at. For example, a movement dataset may contain the movement patterns of all the children from one school. At the beginning of the school day, all of the children will converge onto the school grounds. If the movement patterns could be analysed at a finer spatial granularity, smaller groups of individuals may seem to move from one location to another – these groups could represent individual classes. School children are often grouped into years and, often, each year will have a regular meeting which all the relevant children (i.e., the ones in that year) must attend. If this data cannot be analysed at a suitable level of granularity, these subcollectives may not be apparent.

```
[D1] No members are collectives.
[D2] Some members are collectives.
    [D2.1] Not all members are collectives.
    [D2.2] All members are collectives.
```

8.3 Classification of Collective Motion

The new taxonomy could be applied to the spatial collectives that have been extracted using the set of spatial coherence criteria (Chapter 5) to identify their types. However, the updated taxonomy only analyses a spatial collective based on certain features: membership, location, formation, common location and depth. The collectives have all been identified based on the evolution of the positions of their individuals members. Individual motion could play an important role in distinguishing a spatial collective in forms of its motions. Although yet to be implemented, the remainder of this section discusses two further criteria that could be added to the taxonomy that classifies a spatial collective based on its observed behaviour.

8.3.1 Footprint

One level of the TLA framework (section 8.1) analysed the evolution of the region occupied by a collective (i.e., its footprint). The ways in which a collective's footprint evolves is an important aspect of collective motion and one that may allow a wider range of spatial collectives to be distinguished. The changes that a footprint may undergo is dependent on the granularity at which it is observed but some distinctions can be made irrespective of this. It is assumed that a representative footprint has been determined using a pre-defined procedure. To classify a spatial collective under this criterion the distinguishing features of a footprint must be established: in what ways can two spatial collectives' footprints be distinct? Remember that this criterion only looks at the evolution of the footprint, the movement of the spatial collective has already been considered under the location criterion.

An initial distinction could be made by looking at whether or not a collective's footprint can change in size, where size is be taken as the area of the footprint and measured by suitable units. If the size of the footprint can vary, it can either increase (*expand*) or decrease (*contract*). One may wish to distinguish between the way in which the size of the footprint changes; it may contract or expand but retain its shape (*uniform growth*) or its shape may become deformed (*non-uniform growth).* This latter distinction is qualitative and would require the user to specify what they consider to be uniform or non-uniform growth; similar issues would have to be considered as discussed in section 3.2.2.

```
[FP1]  Constant size.
[FP2]  Variable size.
    [FP2.1] Expansion.
        [FP2.1.1] Uniform growth.
        [FP2.1.2] Non-uniform growth.
    [FP2.2] Contraction.
        [FP2.2.1] Uniform growth.
        [FP2.2.2] Non-uniform growth.
```

As well as its size, a footprint can change shape. The number of possible ways that the shape of a footprint can change is vast and could not be exhaustively included within this thesis. However, some distinctions may be enumerated.

If not discounting changes in size, an initial distinction can be made between those collectives whose footprint can change shape (*variable shape)* and those that cannot (*constant shape*).

Within Wood and Galton [2010b], change in circularity, compactness, elongation and rotation were all suggested as possible salient features of a collective's footprint; these could all be offered to the user as ways to distinguish the evolution of the shape of the footprint. Circularity could be represented by the ratio of an object (i.e., the footprint) to its least bounding circle; compactness represented by the relation between the footprint's perimeter and its area; and, elongation which in two-dimensions will be represented by the aspect ratio of its minimal bounded rectangle (in any orientation). Wood and Galton [2010a] noted the possible difficulty of qualitatively measuring these properties. One could define whether or not the feature is maintained, increased or lost. However, it does not seem appropriate to include these distinctions within the taxonomy provided here. The information may not always be apparent within the data and goes into much more detail than the other criteria.

There is some relationship between some of the features. For example, if a footprint decreases its circularity, it is likely to increase its elongation. Such a footprint may also increase its compactness; however, this need not be true. In contrast, a change in rotation can be considered independently of a footprint's circularity, elongation and compactness. Given this information, it is difficult to present a hierarchical classification relating to a footprint's shape similar to those given to the previous criteria much beyond whether or not the shape is *constant* or *variable*.

```
[FP3]  Constant shape.
[FP4]  Variable shape.
```

8.3.2 External Factors

As discussed within the review of research within movement pattern analysis (Chapter 4), the external factors that may influence the movement of a collective are very important. This criterion would classify a spatial collective according to the environment that the collective exists in. Fundamentally, this criterion would examine the ways in which a spatial collective may interact with its environment. It is important to note that this information may not be available to a user. If only the spatiotemporal records are available then this criterion must be omitted. If, however, the movement patterns are overlaid over a representation of the environment (e.g., a map), then this criterion may be used.

An initial distinction could be made between spatial collectives whose movement is constrained in some way and those that are not. For example, traffic is often constrained to a network, football players to a pitch and a herd of animals to the field that they are kept in. One may argue that the movement of all collectives will always be constrained in some way (i.e., to the geographical space which is being observed). This is true, but this distinction has been included to distinguish between those collectives whose movement is bounded or constrained in some way within that geographical space and those that are not. Compare a flock of birds with a flock of domestic sheep. The flock of domestic sheep are constrained to the field in which they are kept. However, a flock of birds have no such constraint and are free to fly where they wish. If collectives are constrained by their environment, they can be classified according to whether they are constrained by a network (*path constraint*), or by a region (*region constraint*). Traffic has already been given as an example of a collective whose movement is constrained by a network; collectives within a building (e.g., crowds, an orchestra during a performance) are examples of collectives whose movements are physically constrained but not by a network.

```
[E1]  Constrained by environment.
    [E1.1] Path Constraint.
    [E1.2] Region Constraint.
```

A second distinction could look at the ways in which a collective interacts with its environment. This could account for interactions with objects such as in the work presented by Batty et al. [2003], or if present within the dataset, interactions with other collectives. For some applications this may not be suitable; however, it could allow different types of spatial collective to be distinguished based on their behaviour. Consider a football match. This event could be thought of as comprising two different collectives (i.e., the two teams) each acting in opposition to each other – they are each trying to get the ball to the relevant goals which are in opposite directions. In a similar way traffic on a two-way road could also be considered as acting in opposition to each other.

Some of the research reviewed in Chapter 4, indicated different possible interactions between individuals [Reynolds, 1987; Eftimie et al., 2007; Batty et al., 2003]. Further research is needed to fully enumerate the different ways collectives can interact with each other and with objects that exist in their environment. Presently, it is only noted that these two interactions are possible and that spatial collectives may, or may not, act in opposition to each other. This criterion is clearly subject to both the spatial and temporal granularity at which the movement patterns are being observed.

8.4 Discussion

The taxonomy included within this Chapter is not intended to be complete; it has been provided as an indication of the different types of spatial collective that may be extracted from a dataset using the method proposed in Chapter 5. Unlike the general taxonomy of collectives, it is very difficult to evaluate this taxonomy using theoretical examples; it really needs to be applied to multiple datasets which contain different examples of collective motion to see if they can discriminated. Therefore, some important points should be noted and, where necessary, discussed.

8.4.1 Dependencies

Similar to the general taxonomy presented within Chapter 3, it has not been possible to identify dependencies empirically, only theoretically. The same systematic approach has been taken to identify the dependencies within this taxonomy as in section 3.4.

Within the previous taxonomy, three possible dependencies were enumerated; two of which are not relevant to this taxonomy since the criteria to which they relate are not included within this taxonomy. However, in contrast to the previous taxonomy, many more dependencies can be considered between the criteria that form the basis of the taxonomy of spatial collectives.

Section 8.2.2 noted that a spatial collective may not be assigned a location if its members only intermittently shared a common location, or if the members had similar movement parameters but were too widely distributed through space to be considered to have a location. If a member of a collective cannot be assigned a location, it must be a collective itself. Therefore, similarly to the general taxonomy, a collective of type L1.1 must be of type D2.2.

The formation criterion analyses the relationship between the positions of the individual members of a collective, thus implying that the individuals must have a physical location; if the members cannot be assigned a location, their formation cannot be considered. If the members of a spatial collective cannot be considered as occupying a location, you cannot consider their formation. You could state no formation but this is under the category F2.1 which states the motions of the individuals are qualitatively the same. If the individuals do not have a location, you cannot consider their motion. Therefore, F1 also seems inappropriate because it implies that the individuals have motion to exhibit. Thus, collectives of type L1.1 cannot be classified under the formation criteria.

If the members of a collective are considered as having fixed locations, they must always maintain the same relative position to each other (i.e., have a constant formation (F2.2)). This suggests that if a collective is classified as L2.1.1 or L2.2.1 under the location criterion, it must also be classified as F2.2 under the formation criterion. However, it could be considered odd as considering the formation of the members of a spatial collective considered as L2.2.1; these collectives have variable location whilst the members are fixed (e.g., a mexican wave). It is questionable as to whether these type of collectives can be identified within a movement datasets but has been included as a possibility. If the collective's location is variable but the members are fixed, how would the collective be classified under the common location criterion? This criterion classifies a collective according to the locations that are occupied by the collective's members. This example illustrates the affect of temporality on the spatial collective but also the effect that an interpretation of a collective's description may have on classification: the description, 'a Mexican Wave' may refer to the members at that present time (i.e., a *de re* interpretation) or, all individuals that have created the phenomenon (i.e., a *de dicto* interpretation).

To be identified as a spatial collective, a group of individuals need not ever share a common location; for example, a group of individuals could have been found to have similar movement parameters but be too widely distributed throughout the space to be considered as having a location. Therefore, it is possible to classify a collective that does not have a location under the common location criterion. However, if both a collective and its members never have locations, they must be of type CL1, an individual must have a location to calculate its movement parameter such as speed and direction.

One could state that if a collective occupies a fixed location but its members' locations are variable, the individual members always share the same common location. Although at certain levels of granularity this is true, it may not be at others. For example, if common locations have been identified using the grid method outlined in Chapter 5, it is possible that a collective is located over two grid squares; if this is not recognised as one collective, and the individuals move around the region occupied by the collective, those individuals would not necessarily be considered as occupying the same common location.

8.4.2 Second-order Collectives

The previous taxonomy suggested that a base-level and depth should be specified by the user to determine how many levels of members were to be considered. Given that the taxonomy presented in this Chapter will be applied to spatial collectives, where only the movement patterns of their members are known, the number of levels of members that can be considered depend on the level of detail that is contained within the movement patterns. It seems unlikely that anything higher than a second-order collective could be found within the data set.

8.4.3 Reincarnation and Termination

The taxonomy allows spatial collectives to be classified under the assumption that their identity is known. What is yet to be answered is when a spatial collective is considered to cease to exist and if reincarnation is possible?

These two questions are problematic: one could specify a number of snapshots after which, if a collective exhibits no spatial coherence for this period, that collective would cease to exist; a statement of whether or not reincarnation could also need to be chosen. However, these are decisions that cannot be made here – any such values would be very arbitrary. This research aims to identify the presence of collectives within a dataset with no specific domain or application in mind. Whether or not a collective ceases to exist after a certain number of snapshots, are specific to an application and, as well as if reincarnation should be possible, are both questions that should be answered by the user.

8.4.4 Intentionality

As stated within section 8.2, the coherence criterion has been omitted from the updated taxonomy since it is unclear whether the necessary information would be available. The criterion had focused on the source of the coherent behaviour of a collective and distinguished between purposive and causal collectives. The former generally relied on members of a collective which could be ascribed intentionality. Further research may reveal this information can be extracted from a movement dataset (i.e., the whether an individual can be ascribed intentionality and, if so, what their intentions may be); but these questions have not been addressed within the research presented within this thesis.

8.4.5 Collective Motion

An extension to the updated taxonomy has been presented that classifies a collective based on its behaviour. However, what the different types of spatial collective are that can be distinguished from their behaviour, specifically movement behaviour, has not been addressed within this research. Examples of the different types of collective would need to be analysed to see if they do exhibit distinguishing behaviour; however, this would need to be exhaustive and is currently left for further work. If it is possible, the collectives that have been identified within a dataset using the proposed method could be further classified to establish their type.

The TLA framework provides a way of analysing collective motion to take account of each of the three aspects of that motion: the motion of the collective when considered as a single unit, the evolution of the footprint and the motions of the individual members. To a degree, the location criterion considers the motion of the collective when considered as a single entity. The footprint and formation criteria considers the remaining two levels found within the TLA framework. However, the location criterion only states whether or not the collective is moving, no detail is given on the type of motion that is exhibited. Similarly, the formation criterion can only provide high-level distinctions of how the individuals' positions may be related but with no detail on their specific movement parameters. The footprint criterion does consider the evolution of the footprint in more detail but minimal distinctions have been enumerated. This additional information could be provided by including the episodes that are part of the TLA framework within the taxonomy of spatial collectives; the episodes could help distinguish the different behaviours that are typical of the different type of collectives. However, only an initial list of these episodes have been provided [Wood and Galton, 2010a]. Further research is needed to produce a more comprehensive list and identify the spatial collectives that typically exhibit the various combinations of episode types.

8.4.6 Intensional *vs.* Extensional

Within Chapter 3 a discussion was presented as to whether the initial distinction should be between extensionally and intensionally defined collectives. The only information that is known, regarding the collectives that this criterion is being applied to, is the evolution of each member's position. A group of individuals will have been highlighted as a possible spatial collective because they satisfy at least one of the spatial coherence criteria. Therefore, all the collectives that have been identified could be considered to have been defined in intension. Indeed, it could be argued that it would not be possible to identify an extensionally defined spatial collective from movement data alone. If a group of individuals were supplied with tracking devices, and only the movements of those individuals were analysed, the group could be defined as an extensionally defined collective. However, this research is not taking this approach – movement patterns are being observed of multiple individuals to see if any of them satisfy any of the spatial coherence criteria, and therefore, can be said to be a possible spatial collective.

8.5 Conclusion

A taxonomy of spatial collectives has been presented to indicate the different types of collective that may be identified within a movement dataset. The criteria that form the basis of the taxonomy include information that indicates how a collective has been identified using the method proposed in Chapter 5.

The taxonomy is not intended to be exhaustive but does highlight the wide range of different spatial collectives that may exist. Further research would allow the taxonomy to be evaluated by applying it a wide range of different datasets.

9 Discussion

The ultimate aim of the research presented within this thesis was to develop a method that allowed a collective to be identified within a movement (i.e., spatiotemporal) dataset. This was broken down into the following:

- clarify the possible meanings of the term *collective* and determine the different types that exist;
- construct a general taxonomy of collectives;
- identify and characterise spatial collectives as opposed to general collectives;
- develop a method for identifying collectives within a movement (i.e., a spatiotemporal) dataset;
- propose an updated taxonomy which deals only with spatial collectives – this taxonomy could be applied to the collectives that have been extracted from a dataset to indicate their type.

This Chapter will examine whether the aims have been achieved. A direct comparison is given between the stated aims and the work presented in this thesis (section 9.1). Section 9.2 outlines any limitations that have been noted. 9.3 discusses how the work will be extended in the future.

9.1 What has been presented?

This section will directly compare each of the original aims with what has been presented; in many cases, research questions have arisen that require further discussion.

9.1.1 The General Taxonomy of Collectives

Each of the aims of the thesis relied on clarification to be given on what is meant by the term *collective*. A review of the treatment of collectives within the field of applied ontology (Chapter 2), established that there exists no common notion of such a phenomenon. Different opinions were found especially regarding the properties that collectives possess. Therefore, clarification was given on what type of phenomena the term *collective* will refer to within this thesis (Chapter 3). A detailed and fully expanded definition could not be provided – too many different types of collective exist to give a fully encompassing definition. Therefore, a phenomenon was considered to be a collective if it possessed certain properties; what properties it possessed would help to determine the degree of collectivity that it exhibits. Once it was established the phenomena that were being considered, it was possible to identify the different types of collectives that exist. To distinguish between the different types of collective, the properties of the general class of collective were identified: membership, location, coherence, depth and differentiation of role – these five criteria were used to form the basis of a general taxonomy of collectives (Chapter 3).

9.1.2 Spatial Collectives

The taxonomy provided some understanding of the full range of collectives that exist. The overall aim of the thesis was to develop a method that would allow the presence of a collective to be identified within a movement (i.e., a spatiotemporal) dataset. Therefore, a review was undertaken of the relevant research within the field of movement pattern analysis. This review aimed to identify if there were any pre-existing methods that could be used, or extended, to achieve the overall aim of the thesis; however, no such method was found.

To identify a collective one could try to extract those patterns from within the dataset. Definitions of the movement patterns exhibiting by specific types of collectives were found and general extraction methods (e.g., clustering and aggregation), but these did not appear capable of identifying the presence of all of the different types of collective highlighted by the taxonomy – only some of the necessary patterns were known and an exhaustive search to identify the patterns outstanding would be very time consuming. On reflection it was deemed too ambitious to develop a method capable of identifying the full range of collectives that had been shown to exist; it would have required the definition of the different features of the movement typically exhibited by each type of collective. A large number of example datasets would need to be studied – it is not possible to obtain this amount.

An alternative approach to producing a list of movement patterns would be to identify the hallmarks of collectives as a class; what are the general features that are exhibited by collectives and can be extracted within a movement dataset? It was clear that it would not be possible to sufficiently identify properties exhibited by all of the different types of collective that had been identified within the taxonomy. Therefore, a group of collectives were identified whose presence could be identified in a movement dataset. Referred to as *spatial collectives*, these collectives manifested themselves through spatial coherence.

Since they are simply a special class of collectives, in the sense that they were only singled out since they exhibit a certain feature, they inherited many of the features described in Chapter 3 as pertaining to the wider class. However, features relating to membership were reconsidered, thus identifying and characterising spatial collectives as opposed to general collectives. Section 5.1 clearly outlines the characteristics of spatial collectives.

9.1.3 Identifying the Presence of a Spatial Collective

Spatial collectives were singled out since they manifest themselves through spatial coherence; the method to identify their presence within a movement dataset was developed by focusing on this property. The review of research within the field of Applied Ontology highlighted the idea of a unity criterion as a method of identifying the members of a collective. The spatial features of spatial collectives could be used as a unity criterion to identify their members. Three such features were identified: common location, formation and similar movement parameters. Referred to as *spatial coherence criteria*, if some set of individuals satisfied at least one of the criteria, they were considered as forming some kind of spatial collective. The use of the term unity was avoided since the spatial coherence that is being used to identify the spatial collectives is not necessarily their source of collectivity; they are not a specific type of collective but, instead, are a class of collectives that possess a certain feature (i.e., spatial coherence).

Chapter 5 presented the spatial coherence criteria. To evaluate how successful the method was in achieving its aim (i.e., identification of the presence of spatial collectives), the coherence criteria were applied to two datasets with the use of a specially designed computer program, the results of which can be found in Chapter 7.

9.1.4 A taxonomy of spatial collectives

The method to identify the presence of collectives within a dataset has been successfully implemented and applied, but the method does not give an indication of the different types of spatial collective that exist. The general taxonomy of collectives would allow a spatial collective to be classified but not necessarily to an appropriate amount of detail: some of the criteria are irrelevant where others could be expanded. Therefore, an updated taxonomy was presented which identified the different types of spatial collectives one might expect to identify within a movement dataset.

9.2 Issues Remaining to be Addressed

Section 9.1 compares the aims to what has been presented. However, some aspects of this work warrant further discussion.

9.2.1 Collectives

Although it was stated that the properties a collective possessed would determine the degree of collectivity that it exhibits, the degrees of collectivity were not enumerated. The properties relate to the five criteria that form the basis of the taxonomy. For some of the criteria, it is possible for a collective to be considered as not possessing that property (e.g., no location, purely fiat collectives, no formation, no differentiation to roles); it seems sensible to consider these collectives to exhibit a lower degree of collectivity compared to those that do possess the property. Further work could produce a list of all of the possible combinations of these criteria ranked according to the degree of collectivity they are thought to exhibit. However, it is thought that 5550 different combinations exist; if they are to be ranked according to their 'collectivity', examples of each combination would need to be explored. How the degree of collectivity would be quantified would also need to be addressed – it could be considered to be subjective and therefore, very difficult for an individual to definitively specify.

Within Wood and Galton [2009b] and Chapter 3, a collective x was denoted as having a 'membership-defining property' F.

$$Collective_F(x) \rightarrow \forall y, t(Member(y, x, t) \leftrightarrow Part(y, x, t) \wedge F(y)).$$

It is noted in both Wood and Galton [2009b] and Chapter 3 noted that it was difficult to set detailed criteria as to what the range of properties are that could denote membership. The research presented here has not listed any suitable criteria to cover the full range of collectives but could be considered to have addressed this issue in relation to spatial collectives. A group of individuals are considered to be a spatial collective if they satisfy one of the predefined spatial coherence criteria; these criteria could be considered the 'membership-defining property' for spatial collectives.

The taxonomy has received very positive feedback and has begun to be cited and used by other researchers, namely Ong et al. [2010]. Illustrative examples (section 3.3) showed some of the different types of collective that could be classified using the taxonomy, more examples can be found in Wood and Galton [2009b]. However, there are still questions that need to be addressed regarding the taxonomy.

The illustrative examples indicated that it is not always easy to apply the criteria. For example, when classifying general types of collectives such as an orchestra or a platoon, the finest-grained subcategories of the taxonomy may not be suitable. It is suggested within section 3.4 that the user could give a classification using a disjunction or simply not include the fine detail. If a description of a collective is not detailed enough or is ambiguous, it may be difficult to classify that collective using the taxonomy. The user should ensure that they fully understand what they are trying to classify – this may result in a more detailed description being obtained. Although both solutions are not ideal, it is difficult to see how else these problems could be overcome at this stage.

The taxonomy has been developed to include distinctions that we often make as humans – this has led to some of the distinctions that have been included being more qualitative in nature. However, this has led to distinctions that are not necessarily easy to make; notably identifying if a collective can be assigned a location. Currently, it is stated that if a collective can be considered to have a footprint, identifying the region of space that it occupies, that collective could be considered as having a location. A goal of further work is to try and remove, as much as possible, any distinctions that could be considered unclear.

Some researchers within the field of Applied Ontology made a distinction between intensionally and extensionally defined collectives. Chapter 3 contained a detailed discussion of whether this distinction could be included within the taxonomy. However, examples showed that this distinction is very difficult to put into practice. Often a collective is classified according to its description. Unless the description is very clear, it is often very easy to classify it in two different ways depending on whether a *de re* or *de dicto* interpretation is taken. Indeed, it was found that many collectives could be considered intensionally or extensionally depending on the interpretation that is taken; this could make classification of a collective problematic.

It was noted that a solution to the resolution of the problem lay outside the scope of this thesis. However, to try and avoid confusion, a decision was made not to include the distinction between intensionally and extensionally defined collectives within the taxonomy; a collective should be considered as intensional unless the members were explicitly enumerated in the description. Within the updated taxonomy of spatial collectives (chapter 8), it was noted that the focus is on intensional collectives; spatial collectives exist since they have been identified as satisfying at least one of the spatial coherence criteria. Therefore, they could all be considered as being intensionally defined; the only time extensional collectives would be considered to have been identified within a movement dataset is if specific individuals had been given tracking devices and it is the collective that they form which is being classified. However, this is not the approach that has been adopted within this thesis.

The taxonomy is considered to be capable of classifying a wide range of collective phenomena (5550), but this has not been proven empirically; a vast set of examples would need to be collected, ideally multiple examples for each type of collective. A few dependencies have been identified but more could exist. If collected, these examples may also help to identify further dependencies between the criteria and, therefore, unlikely combinations giving a true indication of how many different types of collective exist.

9.2.2 Identifying the presence of a spatial collective

Although positive results were obtained when the proposed method was applied to the two different datasets, questions still need to be addressed.

The synthetic dataset contained 40 boids whose behaviour could be adjusted by setting different values for three parameters: alignment, cohesion and separation. To try and ensure the presence of collectives within the dataset, 20 boids were given parameters to favour the formation of collectives (species A), the remaining 20 were not (species B). These parameters did seem to cause species A to move together as a group and this was successfully identified by the individual-based common location criteria. In contrast, the settings for each of the two species did not result in boids returning or remaining in a certain location. Therefore, the location-based view of the common location criteria identified the locations in which the boids were moving around, but no meaningful information was gained regarding spatial collectives. Given the ways in which a boid's behaviour is programmed, they are expected to move in a similar way to the boids around them; each boid also moved at the same speed. The settings given to the each of the species did not appear to be able to change this. Therefore, you would expect the similar movement pattern criteria to identify the majority of the forty boids as forming a spatial collective. Results indicated this to be true with reasonably low accuracy and precision rates being obtained (table 7.7). With regards to formation, boids try to align their behaviour to those around them leading to patterns such as synchronous change in direction. Setting alignment and cohesion to be low could affect this; however, this was tested when trying to find the most suitable values for alignment, cohesion and separation for each species. It was established that low values for alignment and cohesion did not cause the boids to have less synchronous changes in directions.

The coherence criteria were also applied to a real dataset which contained the movement of ships within the Solent over a twenty-four hour period. Although it was not known whether any collectives existed within the dataset, the proposed method was applied to the dataset as an experiment to see (a) how easily the method could be applied to real data and (2) if any collectives could be found. Results showed that he method could easily be applied to real data and meaningful spatial collectives identified (e.g., port, shipping lanes and pilot stations).

The research presented here does show that a method has been developed to identify spatial collectives within a movement dataset. However, if the proposed method is to be fully evaluated, it must be applied to many more different datasets. An effort was made to collect some more datasets to present here; however, only two were identified. The results from these two datasets seem to be sufficient to prove that the method is successful but, more datasets will need to be collected to understand how they can be used in real-world applications. If more datasets are collected, it is likely that they will have been collected with the use of GPS technologies. GPS records are likely to contain some error [Hoffmann-Wellenhof et al., 2001; Dodge et al., 2009]; this has yet to be fully factored into the implementation of the coherence criteria but is left as a goal of further work.

When the spatial coherence criteria were applied to the two different datasets, the inclusion of a human analyst was very important. Each of the criteria took a set of inputs which could include a cardinality constraint, a snapshot constraint, a search distance, values to determine search space (i.e., for a sliding window approach), and, a percentage. The cardinality and snapshot constraints are values that will usually be known to the user – they know what their application demands. However, this is not always the case when it comes to the other parameters. An analyst is needed to identify which values produce the most meaningful results – sometimes more than one option may need to be tried and the results compared. This process cannot be automated at this present time; as humans, we find it reasonably easy to detect patterns and, viewing the movies that are produced for each criteria by the computer programme, we may easily identify any information that is not being extracted (i.e., individuals that are participating in spatial collectives but they are not being found). It is unclear how this process can be currently implemented, the programme will identify the collectives that satisfy the criteria given its constraints but cannot identify what are the optimum values for these constraints. This is not saying that the method is not able to extract spatial collectives from a dataset but that to do so successfully, it must be given certain parameters that the human knows. Further research may allow this process to become less interactive. For example, a human could give a possible range of values for each input and a probabilistic model could identify what produces the most collectives. However, whether the quantity of collectives that have been identified is a good measure of success is a question that again, can only be answered by a human analyst.

Each of the proposed coherence criteria appears to successfully identify different types of spatial collective – none became apparent that were not needed. However, the criteria have only been implemented in their basic forms. Within Chapter 5 different aspects of each criterion were presented. For example, calculating lagged similar movement parameters and common locations as well as synchronous occurrences. This thesis only presented them in their simplest form to see if the method worked; since this has been proven true, the criteria may be expanded to include all of the ideas discussed in Chapter 5. These additions may also help to distinguish between different types of spatial collectives.

9.2.3 Spatial collectives

Due to a lack of available datasets it has not been possible to fully evaluate the updated taxonomy; however, it has been included to allow further considerations of spatial collectives and indicate how the work presented within this thesis could be extended. Some of the criteria, such as footprint and external factors, need to be researched further to identify how a spatial collective may be classified under this criteria.

9.3 Further Work

The discussion within section 9.1 has highlighted ways in which the work presented here could be extended. This section gives an overview of these areas but also indicates some possibilities that have yet to be mentioned.

9.3.1 Collective Motion

The taxonomy of spatial collectives highlighted that it could be possible to distinguish between collectives according to their movement. This idea has been discussed in previous publications but without the focus on spatial collectives [Wood and Galton, 2009a, 2010b,a].

The Three-Level-Analysis (TLA) framework (section 8.1) was produced to allow the representation of and reasoning about collective motion (the motion exhibited by collectives as a class). The framework took into consideration the way collectives and motion is described. Considered as three levels of spatial granularity, three aspects of collective motion are considered: the motion of the collective when considered as a single entity, the evolution of the collectives footprint and the motions exhibited by the individual members. To account for the importance of granularity in the way motion is described, the TLA framework includes a set of *episodes*: as a maximal chunk of homogeneous process at a given level of granularity. It is possible that the framework could be used to form the basis of a classification of collective motion with a focus on spatial collectives. However, it has not been included within this thesis – it is considered to be a research project within itself and a possible way in which the work presented here could be extended.

The review of movement pattern analysis research involving collectives highlighted that factors external to a collective can influence its movement; for example, objects within the landscape, other individuals or other collectives. Section 8.3 has suggested some possible ways in which these factors could be used to classify a spatial collective but much more could be done. Further research could extend this part of the taxonomy.

Within the general taxonomy of collectives (Chapter 3), it was noted that phases of a collective's lifetime can be classified separately; this allows for the distinct phases in a collective's existence to be considered. Within the spatial coherence criteria that have been presented (Chapter 5), it has been noted that a spatial collective may only exhibit intermittent spatial coherence. This could indicate different phases within a spatial collective's lifetime. If the method was extended to include the extraction of different episode types as suggested within Wood and Galton [2010b], episodes could help to identify the phases of a spatial collective and possibly, what phase a spatial collective is being observed in.

9.3.2 Granularity and Uncertainty

Granularity plays an important role in how a collective and its motion is described; this is highlighted by the three different levels within the TLA framework and the use of episodes. Some of the spatial coherence criteria, to a degree, do allow motion to be considered over multiple levels of granularity, namely where a percentage is requested or dimensions of a sliding window. Some may argue that the distinctions requested from the user are quite arbitrary; however, it is a start. Further work could try to extend this aspect of the proposed method.

Within the TLA framework, three different movement patterns are considered, one for each level within the framework; each level can be considered as a different level of spatial granularity. Little attention has been paid to the relation that exists between these levels and how the information that is extracted at each level varies. This is an open and active research question [Hornsby, 2001; Hornsby and Egenhofer, 2002] and is not limited to the TLA framework. Within the different levels of the TLA framework, different information is likely to become apparent; however, the relation between the information extracted at the different levels is not clear. It is possible that different episodes would be present at different levels of granularity, thorough experimentation may identify episodes that comprise a specific set of episodes when the motion is considered at a finer level of granularity. To answer this research question, a large corpus of movement patterns would need to be analysed at multiple levels of granularity.

The taxonomy of spatial collectives has incorporated the levels found in the TLA framework with the inclusion of the criteria: footprint, formation and location; this could be extended further if a classification of collective motion is produced.

When analysing real datasets, the uncertainty of the data must be taken into consideration. If uncertainty exists within a dataset, a minimum fine level of granularity is imposed. If the user has control over the level of granularity at which the data is being observed, this uncertainty must be taken into account – it would not be suitable to have a fine level of granularity that is lower than the level of uncertainty that exists in the data. The uncertainty may also effect the parameters used in identifying a spatial collective within a dataset. For example, the individual-based common location coherence criteria identifies a spatial collective based on a distance that is given by the user; this distance denotes the proximity that two individuals must be within to be considered to share a location. If there is uncertainty regarding the position of each individual, this would have to be taken into consideration when using their positions to provide a calculation (e.g., when calculating common location).

9.3.3 The Spatial Coherence Criteria

It has already been noted that the coherence criteria have only been implemented in their simplest form. Further work should be carried out in extending the criteria to include the additional ideas that were suggested in Chapter 5. Once completed, the method should be applied to additional datasets.

9.3.4 The Identification of Collectives

Once a method has been fully developed to identify the presence of spatial collectives and their types (i.e., extend the coherence criteria, include a classification of collective motion and a taxonomy of spatial collectives), research can begin to investigate whether the method could be extended to cover the full range of collectives that were identified within the general taxonomy of collectives (Chapter 5).

9.4 Conclusion

A set of aims were outlined in Chapter 1, the ultimate goal of these aims was to be able to identify the presence of spatial collectives within a movement dataset. This Chapter has examined each of these aims and compared them to what has been presented; each of them has been achieved. In completing this work a number of research questions have arisen that lie outside the scope of this thesis. These have been discussed here and an indication given on how this work can be extended.

10 Conclusions

The thesis set out to identify whether or not it was possible to identify the presence of spatial collectives within a movement dataset. In trying to answer this research question:

- clarification needed to be given on what is meant by the term *collective*;
- identify the different types of collective that exist resulting in a general taxonomy of collectives;
- identify and characterise spatial collectives;
- develop a method for identifying collectives within a movement (i.e., a spatiotemporal) dataset; and,
- propose a taxonomy of spatial collectives to indicate the different types of collective that exist.

Chapter 9 compared these aims to what has been presented within this thesis; it was established that the aims had been achieved, and to the best of my knowledge, with the novelties listed below.

- A review of existing research has established that there appears to be no framework that is capable of handling and distinguishing the wide range of collectives that exist. Therefore, a general taxonomy of collectives has been presented that allows collectives to be classified according to five criteria: membership, location, coherence, depth and role.
- A subset of collectives have been identified that manifest themselves through spatial coherence and therefore, by using movement pattern analysis can be identified within a dataset.
- A method has been developed that identifies the presence of these collectives, referred to as *spatial collectives*, within a dataset and the individuals that are participating in that collective. This method has been implemented and tested on two datasets.
- A new framework has been identified, the Three-Level Analysis (TLA) framework, that allows collective motion to be accurately represented and analysed.

There are many ways in which the work could be extended. As a priority, the taxonomy of spatial collectives should be extended to include criteria that allow the different types of spatial collective to be distinguished by their behaviour – this could be achieved by extending and incorporating the episode types from the TLA framework in the taxonomy. The method proposed to identify the presence of spatial collectives must also be applied to more datasets; the results provided within Chapter 7 indicate that the method can successfully identify spatial collectives within a dataset but, if its full potential is to be explored, it must be tested against a broader range of datasets.

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