Towards Intervention and Counterfactual modelling in spatial agents: A simulation of constrained movement at the Observational level

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Abstract

Increased availability of spatiotemporal data has allowed movement studies to shift their objectives from descriptive models to explanations of the underlying "causes" of movement. This paper presents a model, consisting of three conceptual levels of space-time representation for framing movement analysis: 'association', 'intervention' and 'counterfactual'. These are presented within a conceptual cube accommodating both absolute and relative measurements in space and/or time, relationships between observations and methods of enquiry. To ground these concepts, an agent-based football simulation model is presented as a demonstration of the observation level and the properties of the system related to the conceptual cube. This team sport domain was chosen as it represents constrained space and time as well as simplified spatiotemporal object behaviour that serves to effectively reflect on aspects of the conceptual model. Future theoretical developments in computational movement analysis are proposed in light of the model and the associated development of machine learning methods for simulation and analysis addressing the intervention and counterfactual levels of the conceptual cube.

Keywords: Space-time observations, computational movement analysis, conceptual model, counterfactual, agent-based modeling

1. Introduction

The current proliferation of space-time-theme observations has encouraged and potentially enabled science, in a broad sense, to shift its ultimate objectives from descriptive models to explaining the underlying causes of phenomena. Computational Movement Analysis (CMA) is a multi-disciplinary field, dedicated to concepts and methods working with inherently spatio-temporal observations (Gudmundsson et al., 2011). CMA has brought new insight into spatial dynamic processes through summarizing, extracting, and visualizing movement behaviours in various applications (Long and Nelson, 2013). The achievements would surprise one, if science only aimed to summarize and visualize observations in form of associations and patterns. While it is far from satisfaction, if one is concerned with scientific understanding and reasoning, as they have ironically been lacking in CMA. Seemingly it has not delivered the joy of modelling the reasons behind the movement behaviours because a substantial number of its methods are classified as the data-mining algorithms, which ultimately pursue descriptive or predictive models (Han et al., 2011).

Movement studies have recently also stepped into the realm of Artificial Intelligence (AI) to implement 'thinking machines' for analysing movement behaviours. Similar to many other fields, AI has not provided CMA with the power of 'reasoning-models' to explain the underlying causes of movement decisions, simply because AI itself has not as yet acquired such a capability. Admitting the recently successes of AI (e.g., deep neural networks), the favourite tool in the majority of the current implementations is the association that serves the idea of 'jumping to a conclusion' to recognize patterns and produce stochastic models without producing explanations. These belong to a 'function-based' family of AI algorithms that are almost entirely about fitting a function on the data, with no requirement or production of reasoning models. In contrast, the 'model-based' approach, initially funded by the pioneers of AI, involves a representation of knowledge and reasoning (Darwiche, 2018).

To lay the groundwork for discussion and future implementation, the current work presents a conceptual model to draw and map relations among what we see, what we know, and what we aim to know from and about movement processes, representing an advance on established efforts in movement modelling. This paper is structured as follows: Section 2 summarizes the development of a conceptual cube, and the thinking behind it, through a synthesis of observations, inquiries, and formal scientific objectives. This is supported by a short examination of the nature of space and time in order to extract commonalities (2.1), and a reconsideration of the objectives of movement analysis in the light of the conceptual and practical research effort reported in this paper (2.2). Section 3 introduces an implementation of the proposed model in an Agent-Based-Modelling (ABM) simulation, in order to ground and demonstrate a part the conceptual cube's aspects. The paper concludes (section 4), by a discussion and a few suggestions to model the future generation of AI implementations in movement analysis.

2. Space-Time

2.1. Definition in literature

Definitions of space and time originate in the philosophy of physics with the classical relative and absolute approaches. In this duality, relative space is described as attributes of entities, or entities are seen as attributes of absolute space (Couclelis and Gale, 1986). This debate has been reflected in geographic data models through the discrete-object and continuous-field dichotomies (Peuquet, 1984).

From a movement studies perspective, the varying definitions of space and time do not have any solid consensus. Work towards a common definition necessitates a comprehensive philosophical discussion that is beyond the scope of this paper. Despite the disparity, there appears to be a few overlapping areas in relevant fields that could assist achieving a consensus to satisfy both theoretical and applied movement studies (see Langran, 1992; Mark and Frank, 1991; Nunes, 1991; Peuquet, 2002). These commonalities can be succinctly used to, conceptually, distinguish nine (3x3) observation typologies, presented as part of Figure 1. This makes the cover layer of a conceptual cube, with first, middle, and back layers extending space-time observations into causal factors along association ('what'), intervention ('how'), and counterfactual ('why') lines. This three-layer model of operation, derived from Pearl and Mackenzie (2018), is the basis for the key contribution of the presented research, and is explained later on in this section (2.2).

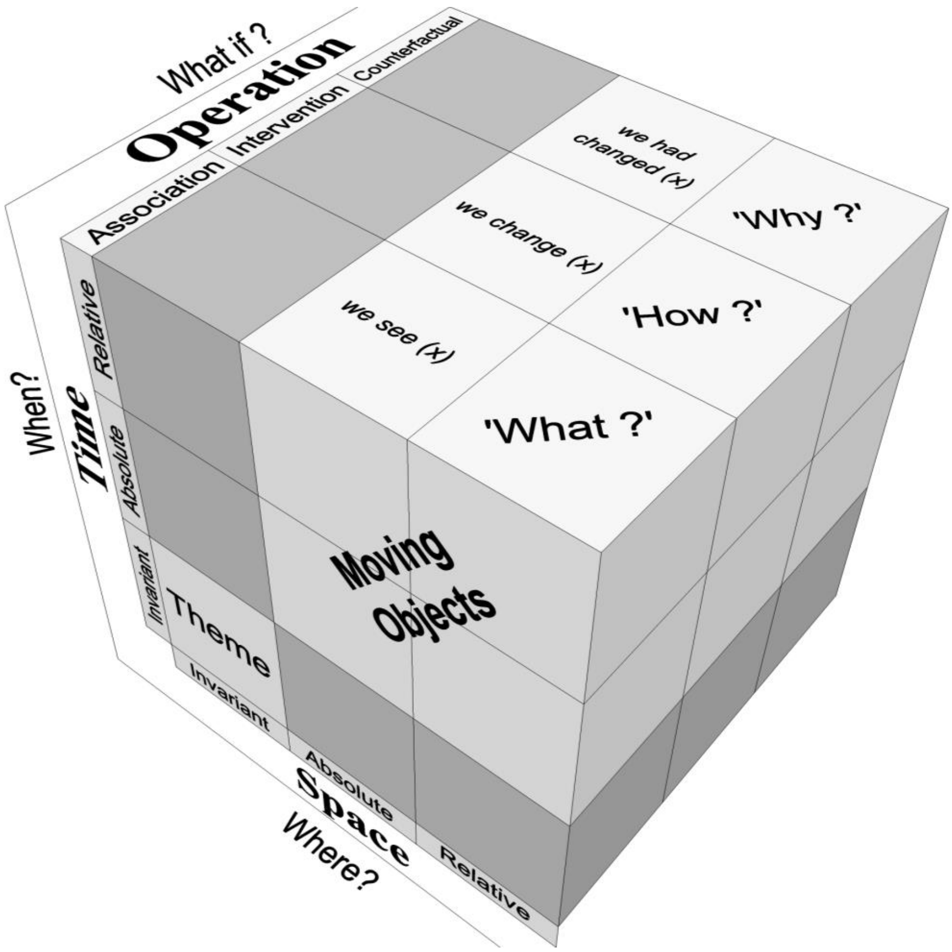


Figure 1. The conceptual representation of space-time-theme observations. An example of temporal observations in invariant column of space could be economic data (e.g. bankruptcy), while a static map (e.g. soil data) is a good instance of spatial data in the invariant-time row.

In short, at the risk of oversimplification, we prefer to assume that relative observations only include measurements that are referenced to Moving Objects' (MO) attributes. Regarding the absolute view in movement data, we assume that space and time measurements are referenced to some constant basis or origin. In other words, referencing to any other entities (objects or events) rather than the MOs embodies the absolute, or at least absolute representation of, space or time (Rahimi et al., 2018).

2.2. Observation and analysis in movement studies

This section explores the Figure 1 conceptual cube, specifically describing the operation axis (levels of analysis). As background, we present an adopted framework of the 'ladder of causation' concept, introduced by Pearl and Mackenzie (2018), which distinguishes three association, intervention, and counterfactual stages of understanding. They claim that the new and underpinning science of causality is established based on three distinct and correspondent levels of cognitive ability: 'seeing,' 'doing,' and 'imagining.'

The authors describe a *seeing* actor – an observer – as an entity capable of sensing its surroundings. Such an observer is qualified to answer various forms of *what* inquiries (e.g., what, when, or where something happened or may happen), or any dual and triple combination of them (e.g., a question of movement for when and where). An observer is also, in most cases, capable of summarising its sensory observations into patterns and associations, which together with mere observing satisfy a few scientific objectives. The scientific objectives are often presented as a set of goals starting from ‘exploring,’ ‘describing,’ ‘changing,’ ‘evaluating,’ ‘assessing,’ ‘understanding,’ ‘explaining,’ and ending with ‘predicting,’ which are mainly pursued by ‘what,’ ‘how’ and ‘why’ question types (Blaikie, 2003). Therefore, the first and second objectives are within the domain of *what* questions and of passive observations, or with some processing, the extracted associations of such observations. In terms of movement data, an observer can detect regularities in our environment and provide answers for such associational questions as in Table 1.

Table 1: Some typical observation and what questions that can be answered by a movement observer.

Relative Time		Where should we expect to see MO i, when its attribute a changes?	Which MO will turn right, when MO j turns right?
Absolute Time		If we see MO i at time t, how far away are we likely to observe geographic object o?	When does MO i meet MO j?
Invariant Time	What can attribute a be if we observe b?		
	Invariant Space	**Absolute Space**	**Relative Space**

In Pearl and Mackenzie’s framework, the ‘intervening’ ability distinguishes an observer from a ‘doer’ – ‘tool user’ – which entails choosing among alternatives to make changes at will. Controlled interventions – active observations – can be applied at all scales, with experimenters able to make changes to some elements of nature to observe, *evaluate* and *assess* the effects of such interventions. Thus we perceive *how* the phenomenon occurs, which is a part of a greater effort to initiate the researchers’ idea of causal relations. In this perspective, the quest to find laws of nature is more than observing the objective facts, and calls for a creative invention and clever testing of hypotheses. Regarding movement analysis, an organism possessing *intervening* ability is capable of providing answers for some typical questions, given in Table 2.

Table 2: Some typical *intervention* and how questions that a doer organism can potentially answer.

Relative Time		If I make MO i move, how long after will MO j start acting?	How can I possibly make MO i follow MO j?
Absolute Time		What would happen if I put geographic object o next to MO i at time t?	Where would MO i be at time t if I ask MO j to leave?
Invariant Time	What would attribute a be if I change attribute b?		
	Invariant Space	**Absolute Space**	**Relative Space**

The third level of understanding concerns *counterfactual* thinking that permits, and calls for, imagination. Stepping into the realm of causation means mastering the science to *understand how* to make a natural phenomenon happen and finally to *explain why* such a phenomenon behaves the way it does. The scientific models of causality rely on a set of possible outcomes – counterfactuals – that are based upon a set of conditional criteria and an intervention, where at least one of the criteria is manipulated (Heckman, 2005). A theoretical explanation of causes and effects and an answer to *why* both come from comparing the counterfactual worlds to the observed one. To take a few out of many possible examples, in movement analysis, a counterfactual reasoner should potentially be able to ask and answer such questions as demonstrated in Table 3.

Table 3: Some typical *counterfactual* and why questions in CMA.

Relative Time		Would MO j have been in location l if MO i had not moved?	Why does MO i follow MO j?
Absolute Time		Is geographic object o the cause of MO i running?	What if MO i had not met MO j at time t?
Invariant Time	What would have been attribute a if I had changed attribute b?		
	Invariant Space	**Absolute Space**	**Relative Space**

The given set of examples at each operation level includes *what if* queries, and claims to scientifically offer answers to such questions at all stages of understanding, albeit with different levels of flexibility. This frames the basic distinction between forecasting and predicting in practical studies. Forecasting, in general, relies on passive observations and fixed conditions, not necessary based on a deep understanding of a phenomenon's behaviour. Whereas predicting a mechanism's reaction to a specific change, synthesised or natural, requires an in-depth understanding of its characteristics (Turchin, 1998).

3. Demonstrating the space-time observation through a simulation

To ground the conceptual model, an agent-based football (or soccer) simulation is presented as a demonstration of the observation-associated space-time properties. In Agent-Based-Modelling (ABM), individual MOs are synthesized to reproduce their interrelationships and regenerate their interactions with the environment within which they move (Bousquet and Le Page, 2004). Agents are the abstract representations of real-world entities (objects and events) that potentially possess characteristics, knowledge, and desires, influencing their decisions in achieving a set of objectives (Moore, 2011). A team sport domain is chosen as it features constrained space and time that serves to effectively reflect on aspects of the conceptual model. We have chosen NetLogo to implement the model as it simply manifests both MOs and environmental objects in the form of 'Turtle' and 'Patch' agents. Turtles are (point) objects, capable of moving over a grid (space) of patches, which are also programmable agents. All agents interact with each other and perform various tasks concurrently (Tisue and Wilensky, 2004). In our case, turtles represent player agents and the ball, where a group of patches collectively create the football pitch and its elements (e.g., goals and boundaries).

A football match can be simplified through a set of spatiotemporal rules based upon some specific assumptions. These rules, presented in an agent decision tree, are shown in Figure 2.

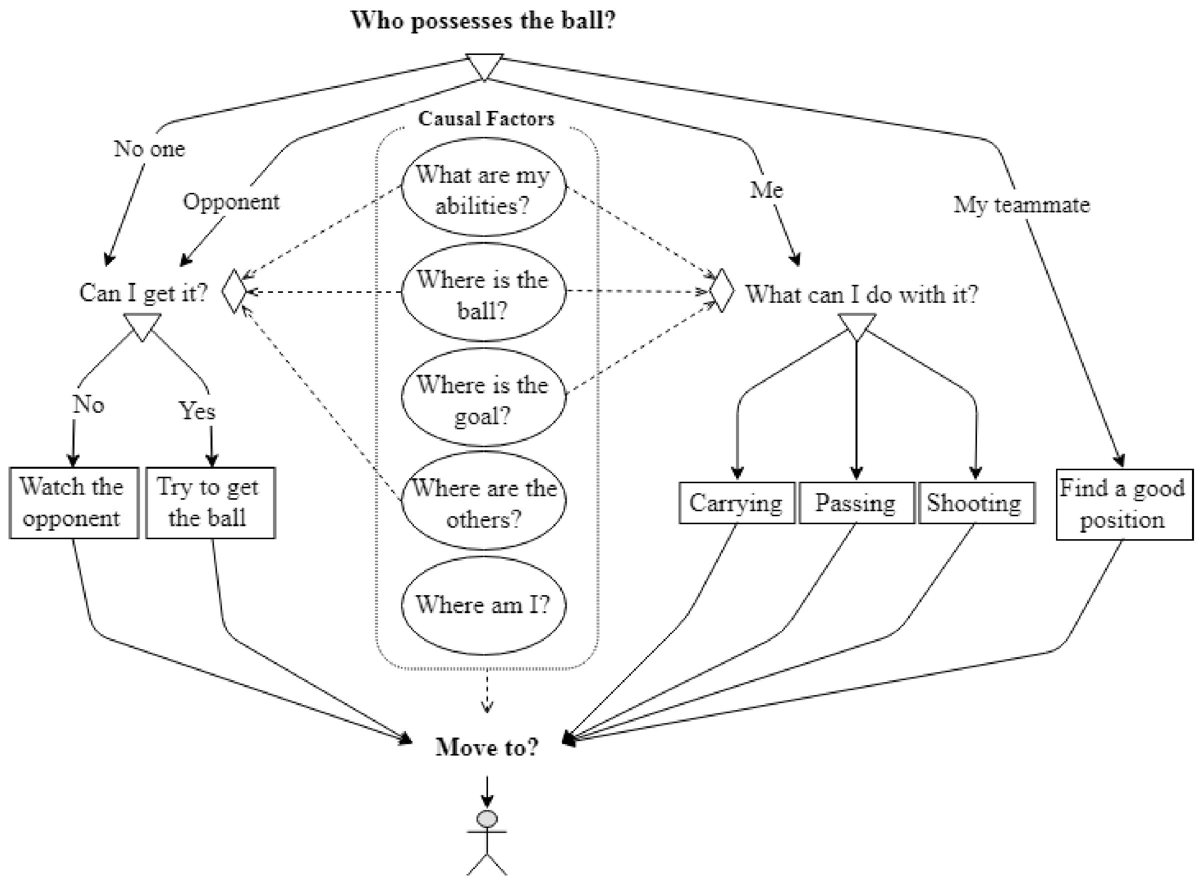


Figure 2: The set of rules in the simulated football decision making process.

In Figure 2, each agent's decision-making process consists of four scenarios, based on the question *Who possesses the ball?* 1) if the answer is one of the *Opponents*, the agent considers *Can I get the ball?* If *No*, agents *Watch the opponent*, otherwise they *Try to get the ball*. Yes or no answers depends on the current agent's abilities, the ball's position, and other players' locations. 2) The second scenario, *No one* possesses the ball, employs the same rules as in the first one. 3) The third scenario is *My teammate* possesses the ball leads to the action *Find a good position*. 4) The last scenario, where the current agent – *Me* – possesses the ball, is more complex leading to possible *Carry*, *Pass*, or *Shoot* actions with the ball. In this scenario, the agent considers its abilities, the location of the opponent's goal, and other players' positions. All scenarios lead to the same final stage to decide the next location to M*ove to?* This is where agents consider a set of factors contained in their abilities, their distance to the opponent's goal, and other moving agents' positions (players and the ball). They also take their own positions on the pitch into account to act within assumed spatial constraints.

In this model, players are influenced by three (Zero-, First-, and Second-order) sets of factors that, respectively, indicate the effects of the MOs' own theme attributes, space-time context, and interactions between MOs based on their movement behaviours. The first set contains the agents' identities, abilities, goals, and duties (e.g., id, energy, stamina, pace, shooting, agility, teamwork). These attributes are either static or dynamic. Energy level for example is systematically reduced over time as a function of the amount of steps and stamina. However, pace, shooting, and agility are assumed to be static, unless fluctuated during the game due to energy level and the agent's current speed. Pace, shooting, agility, and teamwork, while causing different behaviours, together influence decisions to carry, pass and shoot the ball.

The second set of factors is classified as environmental constraints, including the pitch elements and zones implied by players' roles. A role is associated with boundaries that an agent should mostly stay and move within (e.g., goalkeeper is constrained to the penalty box zone), which collectively create a spatial arrangement or formation of players (Bialkowski et al., 2014). In the specific scenario below, we gave team 'A' the common formation 3-5-2 and 4-3-3 for team 'B' as shown in Figure 3. In this figure, red, yellow and black boxes show Goalie (G), right Central Back (rCB), and left Forward (lF) role areas for player 1, 4, and 9, respectively. The purple, grey, and blue boxes represent left Back (lB), right Mid-Fielder (rMF), and Central Forward (CF) role domains, respectively, for player 14, 18, and 20.

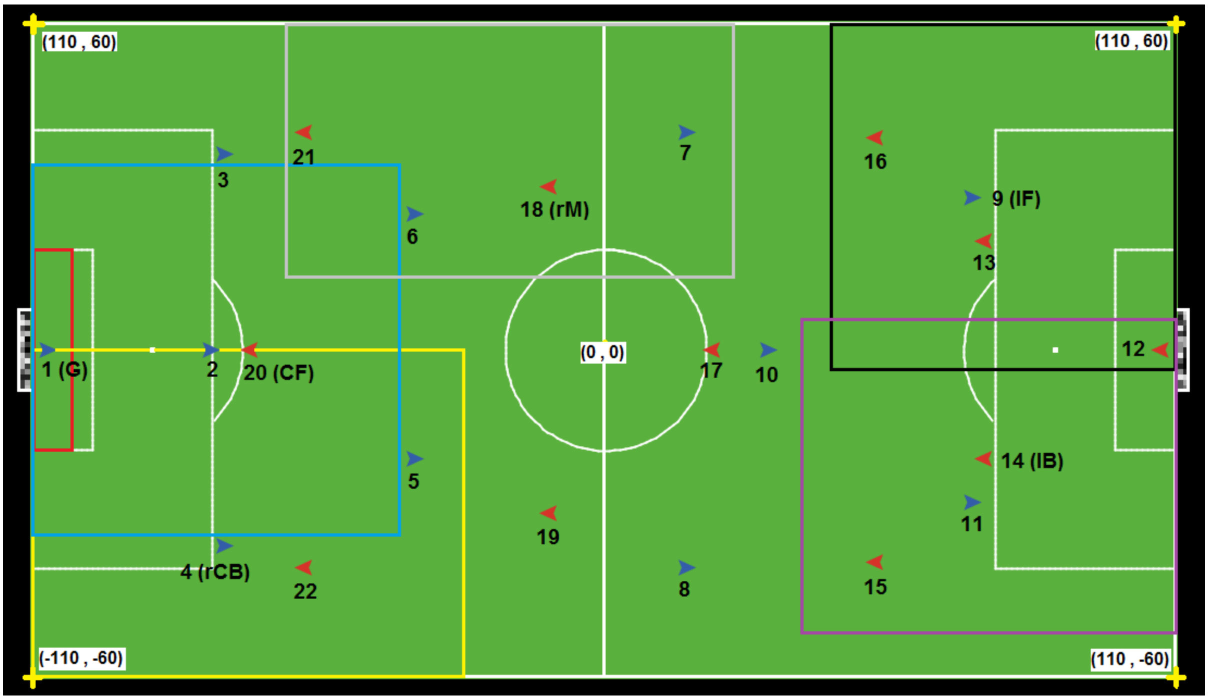


Figure 3: Six examples of the assumed spatial restrictions for agents. The measurements are relative to a Cartesian coordinate system with the origin point at the middle of the pitch. The horizontal axis (x) is between -110 to 110, while the vertical axis (y) is within a range of -60 to 60.

The last causal set of factors involves interactions with other agents (players and the ball). Interaction with other players is either following or running away from them. Trying to get, passing, shooting, and carrying the ball are considered generic interactions between players with the ball agent.

3.1. Simulation model Verification and Validation (V&V)

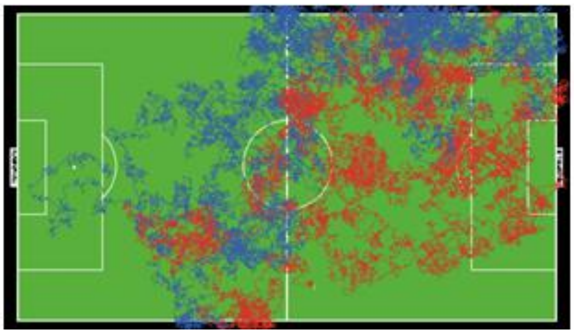
As a part of 'implementation verification' (Sargent, 2010), four simple statistical and visual tests are conducted here to evaluate that agents follow the given decision-making process in Figure 2. These examinations, designed to verify agents' behaviours, are; 1) initially based on random walk, 2) limited with agents' movement abilities (both in line with 0-order behaviour), 3) restricted within the spatial constraints (1-order behaviour), and 4) plausible, given the results of interactions with their neighbouring agents (2-order behaviour).

Note that in all series of tests the model is only run for one half of a game (45 simulated minutes). Considering the observation interval, 10 frames per second, the model produces a sufficiently large data set for verifying its functionality. Specific to the first two tests, only two agents were used to facilitate the presentation of results. However, four agents (all players) were necessary for the third test and five agents (four players, one ball) used for the last test.

We start with testing normality of each player's speed and direction during the game to verify their random-walk. There is no restriction at this level except players should choose their speed (up to 2 pixels[1]) and turning[2] (up to 360 degrees) values at each time interval (100 milliseconds). Figure 4 demonstrates these values are normally distributed for both players. The trajectories, plotted in the middle, are entirely random with no external stimulus (role-based zones, other players).

Player 1	Turning	Speed
Mean	179.6	1
Median	180	1
StDev*	103.49	0.58
Kurtosis	-1.19	-1.2
Skewness	0	0
Min	0	0
Max	359	2

*StDev = standard deviation



Player 18	Turning	Speed
Mean	179.16	1
Median	178	1
StDev	104.45	0.58
Kurtosis	-1.2	-1.19
Skewness	0.01	0
Min	0	0
Max	359	2

Figure 4: The results of testing normality and randomness of the model.

The second test analyses that agents' movement have been limited within the speed and turning thresholds, based on their given abilities (e.g., energy, stamina, pace, and agility). Figure 5 represents the emerged trajectories in that Player 1 (in blue) has moved across almost all the pitch, while Player 18 (in red) has acted more in a circular pattern. This is because of the greater agility of Player 18 that provides it with a broader range of turning angles. In this figure, the graph shows the energy consumption trend for both agents during the game. It seems Player 1, due to less running distance covered, has lost almost 20 per cent less energy than the other player. Also, in fact, Player 18 has a small value of stamina that is the case for consuming more energy.

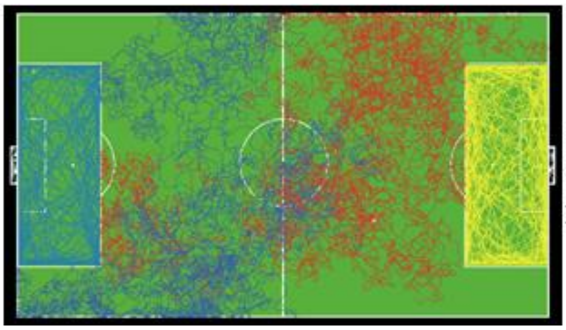
Figure 5: The results of testing agent's endogenous abilities on their movement behaviours.

Figure 6 displays the results of the third test and the effect of role-based boundaries. All four agents are aware of the spatial constraints and only move within their assumed role areas. The descriptive parameters conform to the plotted trajectories. In this test, Player 7 and 18 were chosen as forward players, while Players 1 and 12 were goalkeepers, remaining in the penalty boxes.

[1] Each pixel is equivalent to 0.5 metres

[2] Change of direction

	Player 1		Player 7	
	x	y	x	y
Mean	-88	-2	-32	-12
StDev	11	26	28	36
Range	32	79	148	121
Min	-104	-39	-105	-60
Max	-72	39	42	60



	Player 12		Player 18	
	x	y	x	y
Mean	88	1	25	8
StDev	11	26	38	31
Range	32	79	178	117
Min	72	-39	-72	-56
Max	104	39	105	60

Figure 6: The generated trajectories by player 1 and 7 (light and dark blue) as well as player 12 and 18 (yellow and red).

The last set of tests goes deeper into the model to verify that agents' interactions comply with the given simulation model specification. Here the aim is to see if players still exhibit their abilities and constraints while interacting with spatial objects (e.g., other players, the ball, and the goals). In doing so, at each time-interval or tick, players should make a decision to pick an action from seven options, and decide their velocity in accomplishing the action. Actions include the six discussed operations in Figure 2 in addition to a random-walk action, which guarantees a degree of freedom for agents. Similar to the previous test, Player 1 and 7 are the goalkeeper and a forward player in team A, while players 12 and 18 have the same roles in team B. In this test, goalkeepers are restricted within their half of the pitch, whereas forwards can move across the whole pitch except their own penalty boxes. Figure 7 illustrates the results of the last test.

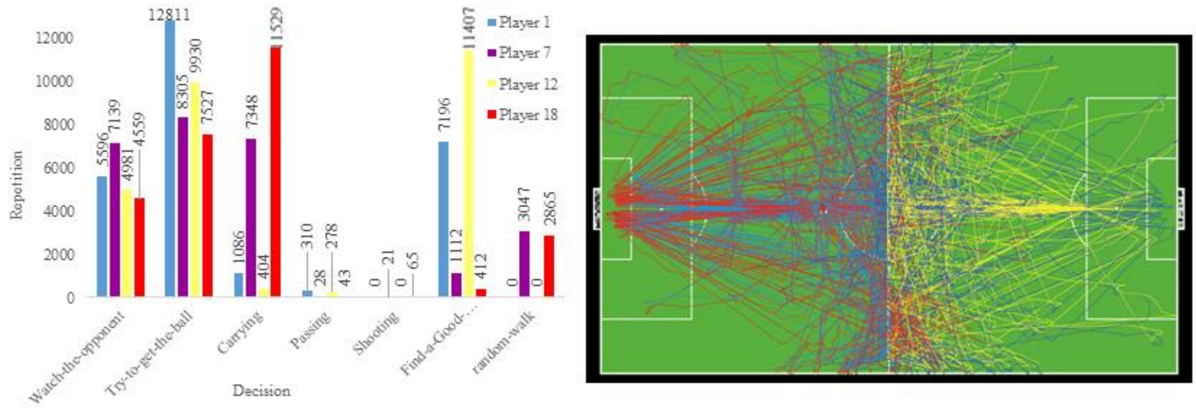


Figure 7: The emergent results of testing agents' interactions.

The bar chart shows how many times each player has picked different actions. It appears that Player 18 has decided to carry the ball more than the others due to having the highest value of speed and agility, which according to the provided instruction were two key parameters for such an action. Player 1 in contrast has tried to get the ball in 45% of its decisions, roughly equivalent to the time that the opposing Player 18 was carrying the ball. Player 12, in interaction with its teammate 18, has looked for free space to open up the game for almost the same amount of time. According to the assumed instruction, teamwork ability is the main parameter for the passing operation, which justifies more passes for players 1 and 12. Players are also supposed to be able to shoot the ball only when they are located in the vicinity of the opponent's goal. The zero number of shoots by goalies, despite their higher shooting abilities, verifies that the rule is being followed and an awareness of surroundings. The emergent space-time behaviours are also summarized in the plotted trajectories in Figure 7.

4. Discussion and Conclusion

In an attempt to develop a model that supports both theory and application, we assumed three (space, time, and theme) attributes to be measured within two conceptually different (absolute and relative) reference systems that are being processed through three (association, intervention and counterfactual) operation levels. This assumption supports unifying 27 possible operations in a conceptual cube (Figure 1) as an arena where each space-time-theme inquiry and its relevant objective takes place.

We simulate the above assumption in order to convey this distinction at the observational level. Figure 2 illustrates the movement decision-making process of a football match in the ABM environment. This model implements 23 agents (including 22 players and a ball) that make choices among 7 operations and decide their speed and direction considering three sets of conditional criteria: 1) their abilities, 2) their responses to the contextual entities, and 3) their interactions with other MOs. The observed behaviours confirm that the agents are aware of all three sets of factors. Tracing the emerged trajectories in Figures 4 to 7 also verifies, the more agents become aware of their surroundings, the less they move randomly and behave more interactively.

Further progress in the emergent generation of AI-based applications in CMA needs the development of a widely-accepted framework to embed the ideas and resulting observed behaviours. In trying to extend the boundaries of a conceptual model, we need to consider three sets of descriptive, explanatory, and predictive goals that are sought with what, how, why, and what if questions. Revisiting the function- and model-based approaches in the AI world, models go beyond mere observations and association to include descriptions of hypothetical worlds, generated through theoretical means. Moreover, models facilitate a more in-depth understanding of complex phenomena and are generally more flexibility in dealing with unforeseen circumstances. Thus, scientific explanations and predictions need explicit modelling of causation, which itself requires manipulation of data and imagination of possible outcomes. These map to the notions of intervention and counterfactual operations that together with association are featured in our model as a strategy for extending what AI-based movement analysis can do. A small subset out of many potential questions was expressed here, that ought to be addressed by an entity that is equipped with a reasoning ability (Tables 1 to 3). These instances ambitiously guide an artificial agent in the transition from the associational to deeper layers in the conceptual cube. This would mean, at the intervention level, inferring the rule structure in Figure 2 (rather than it being created and coded prior to simulation), for the football scenario. This may also enable manipulation of conditional movement criteria and comparing generated counterfactual worlds to the observed one.

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