A spatial analysis of Multiplayer Online Battle Arena mobility traces

Emanuele Carlini[1] and Alessandro Lulli[2]

[1] Istituto di Scienza e Tecnologie dell'Informazione (ISTI)
Consiglio Nazionale delle Ricerche (CNR)
emanuele.carlini@isti.cnr.it
[2] Department of Informatics, Bioengineering, Robotics and System Engineering (DIBRIS)
University of Genova, Italy
alessandro.lulli@dibris.unige.it

Abstract. A careful analysis and a deep understanding of real mobility traces is of paramount importance when it comes to design mobility models that aim to accurately reproduce avatar movements in virtual environment. In this paper we focus on the analysis of a specific kind of virtual environment, namely the Multiplayer Online Battle Arena (MOBA), which is a extremely popular online game genre. We performed a spatial analysis of about one hundred games of a popular MOBA, roughly corresponding to 4000 minutes of movements. The analysis revealed interesting patterns in terms of AoI observation, and the utilization of the map by the avatars. These results are effective building blocks toward the creation of realistic mobility models targeting MOBA environments.

1 Introduction

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On-line gaming is one of the biggest entertainment industries and has seen a rise in popularity in the last decade, thanks to the widespread of fast home connections to the Internet all over the world. Such rise has naturally attracted research communities, as on-line games arguably represents the most widespread instance of what can be considered a virtual environment. Among the various genres, Multiplayer Online Battle Arena (MOBA) is one of the most popular in the current landscape of online gaming, targeting both casual and professional e-sport players. Games like Defense of the Ancients (DOTA) 2 [2] and Heroes of Newerth (HoN) [4] created huge communities of players that challenge themselves in countless player-vs-player matches. The business figures around MOBA are impressive and approaching those of classical sports: the most important MOBA related e-sport event, the DOTA 2's International, in 2016 had a prize pool of around $18M being the most prized e-sport event ever [3].

In this paper we present the methodology and the analysis of several spatial features in the movements of *avatar*, the virtual representation of the player in the game, in MOBA games. The analysis is based on around 98 replays of matches from HoN, which roughly correspond to 4 000 minutes of movements in the MOBA virtual environment. In particular, we analysed the following features: (i) how avatars are distributed in the map? (ii) how are populated the Area of Interest (AoIs) of the various avatars? (iii) how many avatars remains alone for a sufficient period of time?

The main intent of such analysis is to provide building blocks for the design of mobility models that capture the essence of movements in MOBA. In fact, one of the most active field of research in virtual environments has regarded the transition of virtual environments from client-server to distributed applications. Such approaches, broadly referred to as Distributed Virtual Environments (DVEs) [20]. The goal of this approach is to improve the scalability and the cost-effectiveness, by orchestrating the support of the virtual environments exploiting computational and network resources of the users of the DVE. In this context, an accurate representation of the movements of avatars is essential to properly design, validate and compare different DVE architectures. Specifically the analysis of AOIs and the position of the avatars provides indication on how many avatars share interests on the same parts of the virtual environment. This is of particular importance especially for those solutions in which the position of the avatars affects the performance of the DVE. For example, in Voronoi-based approaches, the management of the DVE is assigned to the machines where users are playing according to a tessellation of the virtual environment, which depends on the position of the avatars [12, 21]. Upon avatars movements the assignment change accordingly, triggering a reconstruction in the distribution of the DVE.

To foster comparisons and further studies on common grounds, we made the traces publicly available [7].

2 Related Work

The analysis and mining of mobility traces with the aim of deriving common patterns and models is an important and large area of research, which considers both human and virtual mobility. In the context of DVEs, many works has focused on the analysis of one of the most popular and widespread online activity, which is online gaming. A common goal often found in such analysis is the modeling of avatars mobility. This can have two main directions (i) defining tools and mechanisms to easily replicate such mobility, (ii) testing and validation of various DVE frameworks and middlewares. The games subject of analysis of mobility traces have been many and of different kinds.

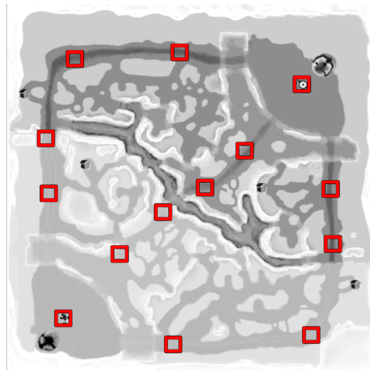
For example, in [15] Liang et al. propose a statistical analysis of Second Life [6] traces as well as a discussion on the implication about the design of a DVE framework. The analysis is performed characterizing both the mobility (avatar speed, pause time etc..) and contact patterns (AOI sizes, etc..), which represent good features when designing a mobility model. BlueBanana [14] is a mobility model for Second Life, in which players gather around a set of hotspots, which usually correspond to towns, or, in general, to points of interest of the virtual world. In [16] and [17] authors provide an analysis of avatar mobility for World of Warcraft [1]. The analysis is focused on a particular area of the DVE where avatars battle for the control of several objectives. The paper presents a modeling of the avatars' behaviors in terms of hotspots, grouping and waypoints. Further, in [23] authors propose an enhancement of the random way point mobility model to better fit the behavior of players in the first person shooting game Quake 2 [5]. Among the features, they added various conditions for an avatar to be stationary, an hotspot popularity and non-straight movement paths.

In the context of MOBA, several works on trace analysis and mining has been recently carried out, due to the massive popularity gained by this online game genre. Few works focus on the modelling of movements in the context of designing AI agents playing DOTA 2 simulating human choices and behaviour, such as in [19]. This work targets a specific MOBA (i.e. DOTA 2) and therefore considers many features that are specific to it. Many works focus on understanding which movement (and sometimes actions) patterns characterizes high skilled players in the context of a MOBA game. Cavadenti et al. [10] built a reference model considering the actions and movements of expert players, and then analyses MOBA traces looking for features that differentiate them from non expert players. Drachen et al. [11] analysed MOBA traces to extract the spatial features of teams as whole, such as the distance between members of the same team and members of different teams, in order to highlight the difference between expert and non-expert players. In a similar way, Rioult et al. [22] analysed several topological and spatial movement features of MOBA traces, trying to find a correlation between the features and the winning or losing. Those works analyzes the traces in order to recognize if the movement patterns have some features that can explain winning or losing in a MOBA games. Even if we share some mechanisms and underlying core principle with some of these works, our direction is different: indeed our analysis is toward those features that characterize the movement essence of MOBA's avatar, with the goal of creating a mobility model that embed such essence.

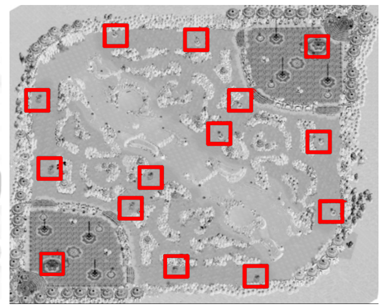
3 Multiplayer Online Battle Arenas

Multiplayer Online Battle Arena (MOBA) is a genre of online games in which players control a single character in one of two factions. The objective is to destroy the opposing faction structures, usually following predetermined paths.

A MOBA map is generally a squared area, in which avatars move mostly along predetermined paths that go thorough faction structures, which, in turn, represent landmarks. Figure 1 shows the map of two popular MOBA games *Heroes of Newerth* and *League of Legends*. Generally, in a MOBA game, avatars start weak and acquire power and abilities over time, by completing various objectives. This kind of advancements affects the strategy of the players with as a consequence on the relationships among players and their movements. There exists several variables that affect avatar mobilities: (i) the phase of the game, (ii) the typology of the avatar, (iii) the level of skills acquired by the avatar.



(a) Heroes Of Newerth.



(b) League Of Legends.

Fig. 1: Examples of MOBA games map, landmarks are represented as squares

The behaviour of the avatar changes during each phase, according to the relationship they have with the other avatars and landmarks.

For what concern the typology of the avatar, these games are played in a modality called 5-vs-5 matches. In this scenario ten players form two teams of five players each. Each player selects an avatar represented by a hero to combat before the real match starts. Each hero has different characteristics. Due to this, each hero is expected to have different play styles and tactics in matches. For example, there are hero called *tanker* who have short-ranged attack ability and excel at surviving combats. Another type of heroes are called *supports* who are weak when alone but can help allies and slow down opponents movements.

Finally, each game is independent from another and avatar starts each game from scratch. The skills of each hero must be improved during the game and the level of them affect the play style and how the avatar moves. For instance, an hero able to increase rapidly its power is probably interested in moving towards the enemy to destroy them. On the other hand, an avatar slow into increase his skills is likely to run away during a fight.

4 The Dataset

In this paper we propose an aggregate analysis of 98 traces from a popular MOBA. The dataset containing all traces, including the data about the AoI statistics and the movement of the player is publicly available [7]. The archive is organized a set of directories, with each directory corresponding to a single trace. Each directory contains three files, whose format and description is presented in Table 1.

The movements happen over a squared map of 15500x15550 points. The AoI of avatars is set at 800 points, as it is the most common range for interaction with objects and other players. The position of the avatars is sampled 20 times per second (once every 0.05) seconds.

file name	*content description*
avatars	Position of avatars at every time frame in csv format **time**: the time frame considered **id**: the id of the avatar **x**: the x-axis coordinate at the frame **y**: the y-axis coordinate at the frame
aoiStatAVG	Aggregated statistics for avatars AOI in csv format **time**: the time frame considered **pop_mean, pop_std**: aoi population average and st. deviation **cr_mean, cr_std**: avatar contact rate average and st. deviation **cd_mean, cd_std**: avatar contact duration average and st. deviation **lone**: number of lone avatars
tessellation	Avatars presence over the map as a grid of 100x100 tiles. Matrix of numeric values

Table 1: Trace format description

4.1 AoI measures

In the dataset we provide an analysis of movement traces in terms of the relationships of avatars among each other by exploiting the concepts of AOIs and avatar contact. To extract these measures we exploited TRACE [8], a tool for the visualization and analysis of mobility traces for virtual environments.

Several of the measures considered can be found in researches related to adhoc networks, especially in terms of *contacts* among entities [13]. In such context, contacts are important as they represent the moment when two entities can communicate and exchange data. Rather differently, from a DVE perspective, contacts among avatars are important, because two contacting avatars share the same spatial interest, and their knowledge can be useful to each other. Therefore, the rate and the duration of contacts can impact both on the design and the behaviour of a DVE architecture. For example, in scenarios in which avatars work as points of centralization for their AOI [9], the analysis of contacts and AOIs are crucial measures. We gather four metrics about AOI and AOI contacts: population size, loneliness, contacts rate and contacts duration.

We define P_a as the set of avatars in a's AOI (excluding a) during an interval period T. AP is defined as the average AOI population for all the avatar in the virtual environment.

$$AP = \frac{1}{N}\sum_{n=1}^{N} |P_n| \tag{1}$$

When $|P_a| = 0$ an avatar is said to be alone, with L being the set of alone avatars. We register an AOI contact when an avatar enters in the AOI of another avatar. We represents with C_a the amount of AOI contacts experienced by an avatar a during an interval period T. The average contact rate CRA is the average number of new AOI contacts experienced by all avatars in the DVE during T, and it is defined as following:

$$CRA = \frac{1}{N} \sum_{n=1}^{N} \frac{C_n}{T} \tag{2}$$

Similarly, the average AOI contact duration CDA is the average of all the terminated contacts of all avatars during T. A terminated contact is registered by TRACE when an avatar exits from the AOI of another one. It is defined as following:

$$CDA = \frac{1}{N} \sum_{n=1}^{N} \frac{\sum_{z \in Z_n} z \times \Delta t}{|Z_n|} \tag{3}$$

where Z_n is the set of all terminated contacts of avatar n.

We record the values for the above metrics during the generation of the traces. Such statistics, are stored in the same archive with the mobility trace itself for later use and comparison.

5 Trace Analysis

In this section we describe how we perfomed the analysis of the traces for the MOBA game "Heroes of Newerth". We start describing the methodology to extract the mobility traces from real game replay and converting them in analyzable traces in Section 5.1. In the remain of the section we describe the analysis we performed on such traces: (i) several details about the traces in Section 5.2, (ii) an analysis about the AoI of the avatars in Section 5.3, and (iii) an analysis on the hotspots identified using the traces in Section 5.4.

5.1 Methodology

In this paper we presents the analysis of 98 traces from the MOBA "Heroes of Newerth" (HoN). The traces have been scraped from replays downloaded from the official servers of the game on April 2012, when the popularity of HoN was at its maximum. We used a Python script to transform the replays into movement traces.

Next, in order to analyse the trace we make use of TRACE [3]. TRACE is a Java software library for the generation of avatar movement traces aimed to an easy integration and portability among different systems and approaches.

We extended TRACE with an additional mobility model called *HoN-Mimic* able to mimic the movements loaded by the replays of HoN. We choose this approach for the following advantages:

- we can compare *HoN-Mimic* with all the mobility models built-in in TRACE;
- we can automatically extract several metrics provided by TRACE;

[3] `https://github.com/hpclab/trace`

– using TRACE permits us to convert the replays of HoN in a format similar to other mobility models for an easier integration in third-party softwares.

In the following we describe the type of data and the information we extracted from the traces.

5.2 Trace Length

In the dataset analysed, the length of the traces varied from 22701 to 91285 frames, correspondent respectively to matches with a duration of 19 to 76 minutes. The average observed duration is of 48124 frames, which corresponds around to 40 minutes. The total duration of observed traces is around 4000 minutes. By analysing the probability distribution histogram of the duration, the best fit is a Nakagami distribution [18] with a shape parameter of 0.62 Figure 2 shows the histograms and the fitting distribution.

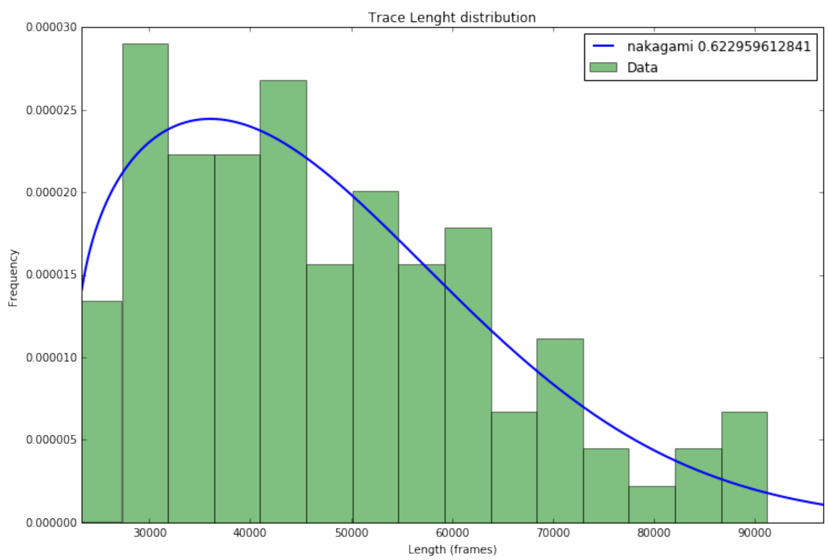


Fig. 2: Distribution of length of the traces

5.3 AoI analysis

We have performed an analysis of the proximity of avatars in terms of their average AoI population AP, as it is described in Section 4.1. The objective of this analysis is to identify how the AoI population changes in the different phases of the game.

To conduct the analysis we have measured the average AP of each trace in every frame. More formally, the value for the global AP_T at the frame n is defined as:

$$AP_T(n) = \frac{1}{N} \sum_{i=0}^{K} AP_i(n) \tag{4}$$

where $AP_i(n)$ is the average AoI population for the trace i at frame n, and K is the total number of traces.

In order to compute a meaningful result of the AP metric it is required that all the traces have the same length. This is due to the fact that if the traces do not have the same length we are not able to compare different traces because the phases of each trace could be not aligned. Therefore, we normalize the traces performing a linear interpolation, such that:

$$y_i = \frac{y_{i-1} + y_{i+1}}{x_{i+1} - x_{i-1}} \tag{5}$$

The results of the analysis are presented in Figure 3. From the images, we can distinguish the phases that characterize a typical MOBA game, as mentioned in Section 3, and how the avatars of different faction relate to each other. Apart from the initial phase, in which all the avatars are clustered together at the start of the game, we can observe the following phases:

- *beginning* (from the 3000th up to the 30000th frame): in this phase each player tries to acquire skills and power as fast as possible, usually traveling alone or together with few components of its faction. Generally in this phase the contact with players of the opposite faction is avoided and battle among avatars are fast. This phase is then characterized by low AoI population (average below 1) and around half of avatar travelling alone.
- *skirmish* (from the 30000th frame up to the 85000th frame): this is the longest phase of the game, in which avatars coordinates in small groups to defeat opponent's structures at the hotspots or battle against other group of avatars. In this phase we can observe a steady increase of the average population with a consequent decrease of lone avatars.
- *final battle* (from the 85000th frame to the end): in the last phase, the majority of the avatars of both the teams aggregate in large groups to achieve the final objective. This phases sees a drastic diminishing of lone avatars and a rapid growth of the AoI population.

5.4 Hotspot analysis

We performed an analysis of the movement of avatars in order to verify if the landmarks in the game, as described in Section 3, actually represent actual hotspots in terms of mobility. Our analysis focus on understanding the position, importance and size of hotspots. To this end, we divided the map into a

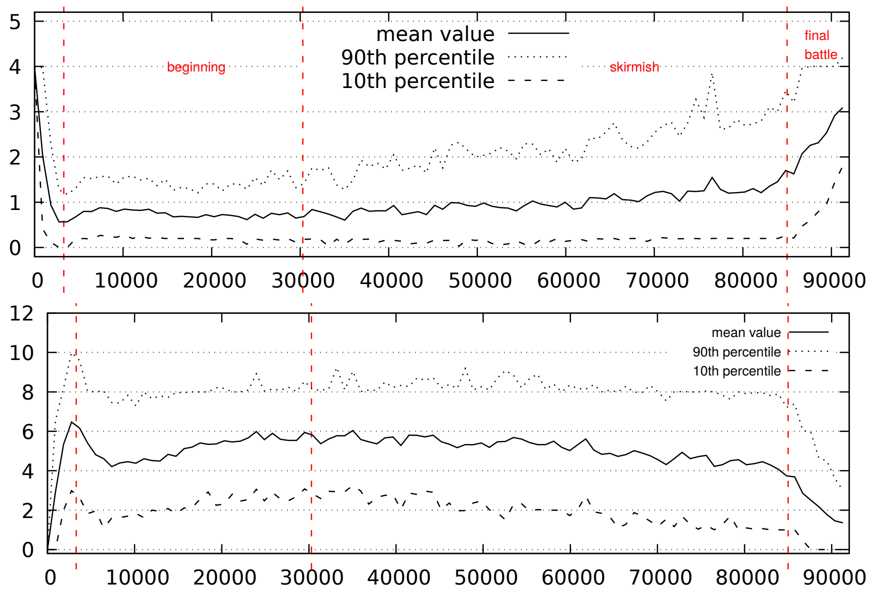


Fig. 3: Average AoI population and avatar loneliness over time

grid of 100x100 tiles, all of the same dimensions. For each trace, we counted the presence of avatars for each tile, and then averaged the count for each tile considering all traces.

Figure 4 presents an heat map depicting for each tile the amount of avatars traveling in that specific portion of the map during the game. It is possible to identify mainly 6 hotspots relative to the following position in game: (i) the two team bases, respectively at the top right and bottom left corner, (ii) the three points where the avatars of opposing teams meet since the beginning (the center of the map, the top left corner and the bottom right corner), (iii) and one more hotspot where "Kongor" is positioned. Kongor is an avatar controlled by the artificial intelligence of the game, it is the toughest unit in the map and killing him gives the team a significant advantage. This is the motivation because this area is usually patrolled by the teams.

It is interesting to note also that the majority of the trajectories of the avatars mainly follow predetermined paths between the hotspots. This observation is important in terms of the design of a mobility model, as it allows to use direct paths from one hotspot to another. It worth to notice that this is the same assumption also made from other mobility models for other games, such as Blue Banana [14] for Second Life.

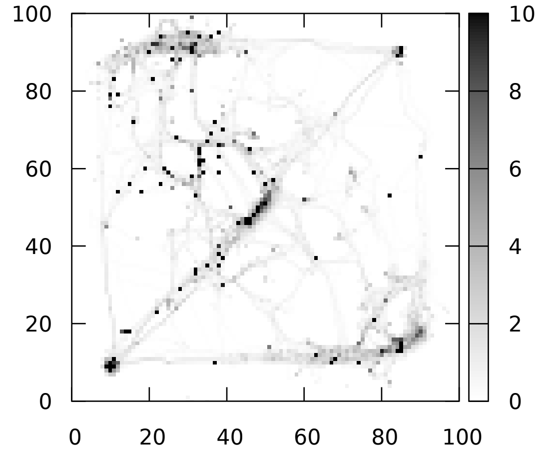


Fig. 4: Hotspot analysis. The heat map represents the average avatar population presence in each tile

6 Conclusion

This paper presented a spatial analysis of movement traces taken from matches of HoN, a MOBA online game. We make use of several metrics in order to detect the characteristics of these games. In particular we identified different phases during a match and how the avatars behave in the different situations. Our analysis span a large number of real traces of the HoN game. We collected such traces and we make them freely available. Our extensive analysis can be a starting point to define novel mobility models able to mimic the behavior of the avatars in the MOBA games. In addition, even if the main motivation of this work is oriented toward the definition of a mobility model, the presented analysis can serve other purposes, such as the creation of AI agents that actually play MOBA games [19], and the inference of the level of ability of MOBA players by the analysis of their movements [10].

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