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# Analysis of Movement Features in Multiplayer Online Battle Arenas

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**Abstract** On-line games represent one of the primary instances of virtual environments, in which avatars share a synchronous and persistent virtual world with each other. A careful analysis and a deep understanding of mobility in online games is of paramount importance to properly design mobility models to accurately reproduce avatar movements. In fact, mobility models of avatar have a relevant impact on the architectural design of virtual environments, especially for those based on distributed and decentralized solutions. This paper analyses around 640 hours of mobility of an extremely popular online game genre, the Multiplayer Online Battle Arenas (MOBA). The analysis has revealed interesting characteristics with respect ot the area of interest of the players and their utilization of the game area. Many of the results confirm the speculations of MOBA players, in terms of the phases of the game and the general behaviours of the avatars. Ultimately, our analysis is aimed toward the creation of realistic mobility models for MOBA environments, as well as the development of AI agents for MOBA games.

**Keywords** mobility model · area of interest · MOBA game · distributed virtual environment · avatar movement

## 1 Introduction

Online gaming is one of the highest revenue industries in the entertainment sector. In the last decade it has undergo a rise in popularity, mostly due to the widespread availability of fast Internet connections worldwide. Such rise has naturally attracted research and commercial endeavors, fostered both from industry

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and research organizations. As a matter of fact, online games represent the most widespread instance of what can be considered a *virtual environment* software application. The Multiplayer Online Battle Arena (MOBA) is one of the most popular game genre in the current landscape of online gaming. MOBAs attract huge numbers of players all over the world and are enjoyed by casual and professional e-sport players. Defense of the Ancients (DOTA) 2 [2], League of Legends [5], and Heroes of Newerth (HoN) [3] are famous instances of MOBA that cumulatively count thousands of matches every day[1]. The business figures around MOBAs are impressive and approaching those of classical sports. The most important MOBA related e-sport event, the DOTA 2's International, in 2017 had a prize pool of around $24 million dollars and is one of the most rich e-sport events ever organized [4].

The aim of this paper is to provide a insightful analysis of the movement features of players in a MOBA game, by analyzing of real-world matches. In particular, our focus is the study of several spatial features in relation with the positioning of the players with respect of their area of interests. The main intent of such analysis is to provide valuable information on the behaviours of avatars for the design of mobility models to capture and reproduce the essence of movements in a MOBA-like environment. In fact, the design of mobility models is one of the most relevant topics of research in virtual environments. The utilization of mobility models has serious implication on the design of an architecture to support virtual environments, especially considering the transition of virtual environments infrastructures from client-server to distributed and decentralized approaches, normally referred to as Distributed Virtual Environments (DVEs) architectures [29, 21].

Players (or *avatars*, their virtual counterpart) participating in a virtual environment share a synchronous and persistent virtual world with each other. In order to enable an engaging experience typical of these applications, the state of the entities in the virtual world, such as avatars and objects, must be replicated in avatars' nodes in a timely fashion. Naturally, each avatar is interested to receive updates for only a subset of the whole virtual environment; this subset is commonly referred to as Area of Interest (AoI). In a centralized virtual environment, the AoI allows to optimize the communication between the server and clients, as well as the visual rendering on the clients. In a DVE the AoI has a more wide impact, as it affects how the connections between the players are created and maintained [9].

Specifically, DVEs can exploit player's resources, such as network and computational power, to improve scalability and cost-effectiveness of the entire infrastructure. A typical strategy is to connect those avatars that share the same interests, which typically has a strong correlation with their position in the virtual environment. This kind of solution is exploited in several decentralized approaches in the state of the art, in which the management of entities is assigned according to a Voronoi tessellation [19, 30] computed by considering the positions of the avatars. A peer-to-peer communication overlay is organized to connect each avatar with the ones in their AoI and the ones whose Voronoi regions share at least an edge (i.e. neighbours). On avatars movements the Voronoi tesselation changes accordingly, triggering a reconstruction in the peer-to-peer communication overlay. In such context, the analysis of AoIs (e.g. how many entities are in the AoI, how long they will stay there) has a great impact on the the design of the DVE ar-

[1] http://steamcharts.com/app/570

chitecture. Clearly, an accurate representation of the movements of avatars with mobility models is essential to properly design, validate and compare such DVE architectures.

This paper is an extension of a previous work, presented by the same authors [11], which performed an analysis on 98 replays of matches from the HoN MOBA game. Such previous work presented a study on the geographical distribution of the avatars in the virtual environment to discover hotspots (i.e. aggregation places), in addition to a preliminary descriptive analysis of several features of the AoI of the avatars. In this paper we extend that previous work in several directions:

- we increment the number of analyzed replay matches to 912 (around 10 times with respect to the previous work), which roughly correspond to 640 hours of game in a MOBA virtual environment;
- we perform a more detailed analysis of the distribution of the AoI population;
- we study the AoI population in terms of stability, i.e. which and how long AoI population values remain constant during a game;
- we analyze AoIs in terms of number of friends and enemies in order to detect the different phases of a MOBA game and to detect the number of crowded situations (i.e. battles) in a MOBA game.

The paper is structured as follow. In Section 2 we present similar works to ours in order to highlight the major challenges in the study of MOBA games. Section 3 presents the main characteristics of a MOBA game making particular attention in how the characteristic of a game may influence how an avatar moves in the virtual world. Next, Section 4 describes how we collected the replays of a popular MOBA game. Section 5 presents our analysis about the spatial features in the replays and Section 6 draws the final conclusions and outcomes of the paper.

## 2 Related Work

The analysis and mining of mobility traces with the aim of deriving models is an important and large area of research which considers both human and virtual mobility. The analysis of mobility is useful in many applicative contextes, such as video surveillance [22, 20], smart-cities [23], community networks [33], and mobile computational grids [8]. In the context of virtual mobility, many works have 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 modelling of avatars mobility, usually with two main objectives: (i) defining tools and mechanisms to practically replicate such mobility, (ii) testing and validating various DVE architectures against realistic mobility patterns.

The modeling of avatars mobility is normally based upon the analysis of real online games traces. The *Game Trace Archive*[2] [18] provides to date 15 different dataset of various online gaming activities (including MOBAs), of which only a fraction contains mobility data. In our previous work, we made publicly available a dataset containing the mobility taken from 98 traces from HoN [10].

The online games subject of analysis of mobility traces have been many and of different genres, with MOBAs being the more studied. In [25] Liang et al. propose a statistical analysis of Second Life [7] traces as well as a discussion on the

[2] `http:/gta.st.ewi.tudelft.nl/`

implication about the design of a DVE architecture. The analysis is performed characterizing both the mobility (avatar speed, pause time etc..) and contact patterns (AoI population, etc..), which are relevant features when designing a mobility model. BlueBanana [24] 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 in the virtual world. Miller et al. [26] and [27] provide an analysis of avatars mobility for World of Warcraft [1]. Their analysis is focused on a particular area of the game in which avatars battle for the control of several objectives, in a way similar to a MOBA game. The paper presents a modeling of the avatar behaviors in terms of hotspots, grouping and waypoints. Further, in [34] 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 [6]. They studied various conditions for stationary avatars, hotspots popularity and non-straight movement paths.

A number of works on trace analysis and data mining has been recently performed for MOBAs, due to the massive popularity gained by this online game genre in the last years. Several works focus on the modeling of movements in the context of designing AI agents playing DOTA 2 simulating human choices and strategies, such as in [16]. Some recent approaches (Sapienza et. al [32], Nascimento et. al [28]) employed data mining techniques to model and predict players behavior in MOBAs. These approaches study the performance of the players in terms of actions and results obtained in the game, such as number of deaths and amount of resources gained, but they do not consider spatial relationship in their analysis.

More relevant with our work, other authors focus on understanding which movement (and sometimes actions) characterizes high skilled players in the context of a MOBA game. Cavadenti et al. [15] 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. [17] 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. [31] analysed several topological and spatial movement features of MOBA, trying to find a correlation between the features and the outcome of the game.

Our work shares some mechanisms and underlying core principles with the state of the art presented above, and in many cases the results are complementary. However, our direction is slightly different as our analysis goes toward the description of those features that characterize the movements essence of MOBA's avatars, with the ultimate goal of creating a mobility model that embeds such essence.

## 3 Multiplayer Online Battle Arenas

Multiplayer Online Battle Arena (MOBA) is a genre of online games in which each player controls a single character (i.e. avatar) in one of the two opposing teams or factions. MOBA's avatar can move on a map normally organized as 2D squared area[3], in which avatars move mostly along predetermined paths littered with buildings, which, in turn, represent main candidates as hotspots. At the start of the game, one team of five players has the base at the lower left corner of the map, while the other team is based at the upper right corner. The avatars at the beginning are grouped in their base. The first team that conquers the opposing team base wins the game.

Figure 1 shows the maps of the MOBA games *Heroes of Newerth* and *League of Legends*. The red squares in the maps represent the main structures where usually the avatars of opposing team meet and combat.

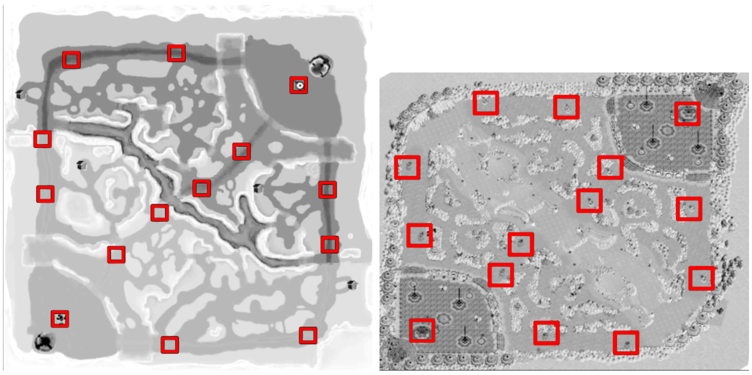
### 3.1 Mobility in MOBA

Generally, in a MOBA game avatars acquire power and abilities over time, by completing various objectives. This game mechanic affects the behaviour of the players, in terms of movements and relationships with other players. There are three main variables that affect avatar mobility: (i) the phase of the game, (ii) the typology of the avatar, (iii) the level of skills acquired by the avatar.

**The phases of a MOBA** A common consensus among MOBA players recognizes three main phases in the game:

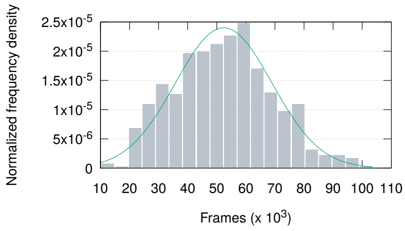
- *laning*: in this phase each player tries to acquire skills and power as fast as possible. The avatars usually travel alone or just with few components of their faction. In this phase battles are generally avoided.
- *skirmish*: this is usually the longest phase of the game, in which teams coordinate to defeat opponent's buildings at the hotspots or battle against other group of avatars. In this phase it is common for a whole team to travel across the map together to ambush opposing team buildings.

[3] alternative map layouts can be found in specific instances of MOBA, but the squared layout is by far the most common one



(a) Heroes Of Newerth. (b) League Of Legends.

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




(a) Histogram of the length values and fitting distribution

| | frames | time |
|---|---|---|
| min | 10K | 8 min |
| max | 103K | 86 min |
| avg | 52K | 43 min |
| std | 16K | 13 min |
| total | 46M | 640 hours |

(b) Descriptive values of the length statistics. Values are approximated

Fig. 2: Analysis of the traces length

– *final battle*: in the last phase, most of the avatars from both teams aggregate in large groups, usually in proximity of one base, to achieve the final objective and win the game.

**Typology of avatar** A classical MOBA game consists of two teams of five players each. Each player selects a *hero*, which has peculiar characteristics that affect its play styles, including the movement in the game area. For example, the so called *tank* heroes have melee attack abilities and excel at surviving in combats. They are likely to stand tall in the middle of the enemies, and usually are surrounded by many other players. Unlike *tanks*, *support* heroes focus on helping allies and usually stay on the sides of the battles.
**Level of skills** During the game the "level" of each hero increases, by participating and winning combats. The higher the level of an hero, the more abilities and options are available during the game. The level of an hero affects also its movements. For instance, a high level hero probably moves towards enemies to challenge them. Conversely, a low level hero runs away during battles and tries to avoid contacts with the opposite faction.

## 4 Data Acquisition Methodology

Our analysis considers 912 replays (around 640 hours of play) from the online MOBA game *Heroes of Newerth* (HoN), downloaded from the official servers of the game on April 2012, when the popularity of HoN was at its peak. The replays come in a binary format, decoded by means of a Python script. The decoding of a replay results in a XML file that contains the position of the players in each *frame*. A frame is sampled every 0.05 seconds. Players move on squared map of $15500x15550$ tiles. The AoI of avatars is set at 800 tiles, as it is the most common range for interaction with objects and other players. By transforming the replays, from a grand total of 1152 replays downloaded we removed those 240 that had some player disconnected during the game.

To analyze the AoI population of the XML data we exploited TRACE [4] [12,13]. TRACE is a Java software library for the generation of avatar movement traces, easy to integrate and port among different systems and approaches. We exploited

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

the features provided by TRACE to create an additional mobility model called *HoN-Mimic* able to reproduce the movements loaded from the XML files. We choose this approach for the following reasons:

- we are able to compare *HoN-Mimic* with the other mobility models that are built-in in TRACE;
- we can automatically extract several metrics provided by TRACE, including the AoI population used in the following analysis;
- using TRACE permits us to convert the replays in a format similar to other mobility models for an easier integration in other software.

An initial analysis of the data regarded the duration of the matches, which updates our previous analysis [11] considering an higher amount of data. A summary of the statistics of the matches duration are presented in Table 2b. Figure 2a shows the duration distribution in frames, which is best fit by a Normal Distribution with $\mu = 52373.53$ and $\alpha = 16613.68$. Note that the following analysis do not considered the matches whose duration is less than 15 minutes ($18K$ frames) as they do not provide valuable information about the evolution of the game.

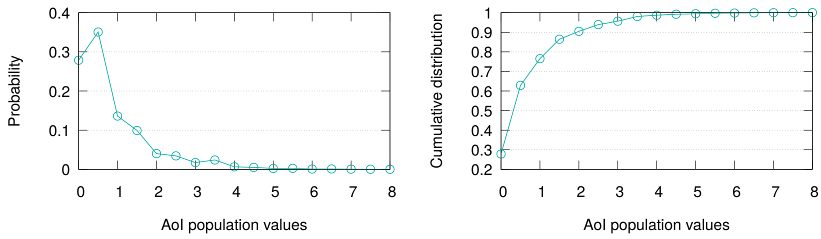
## 5 Trace Analysis

The main motivation in the analysis of movement traces regards the relationships among avatars with respect to the concept of AoI, with the general objective to provide a characterization for the whole MOBA genre. In the context of a DVE, contacts among avatars are important because two contacting avatars share the same spatial interest, having a serious impact on both the design and behavior of a DVE architecture. This often result into having *network overlays* that connect close avatars in order to optimize the delivery of game state updates. For example, in scenarios in which avatars work as points of centralization for their AoI [14] by disseminating the game state of the entities to the other players, the analysis of the behavior of the AoI is a crucial information.

In the remaining of this section we present the analysis of the replays discussed in Section 4. In particular, we concentrate on several features about the AoI: the AoI population (Section 5.1), the AoI population stability (5.2), and the AoI population differentiating between friends and enemies (5.3). Next, we present how it is possible to estimate the number of battles in a MOBA analyzing the AoI of the avatars in Section 5.4 and finally we present an analysis about the hotspots in Section 5.5.

### 5.1 AoI population

This analysis is divided into two steps: the first step observes the frequencies of AoI population values, while the second provides a characterization of those values in correlation with the phases of the game. To evaluate the frequencies of the AoI population values, we consider the average AoI population value for each frame. More formally, we define $P_t^a(r)$ as the AoI population value for a given avatar $a \in A$ (excluding $a$) at the frame $t$ for the specific replay $r \in R$. When $|P^a| = 0$ an avatar is considered an *alone* avatar (in the following we refer to $P$ as a generic AoI




(a) PDF of $K_t(r)$ (b) CDF of $K_t(r)$

Fig. 3: $K_t(r)$ probability and cumulative density functions computed for all replays

population value). The average AoI population value for a frame $t$ and a replay $r$ is defined as:

$$K_t(r) = \frac{1}{|A|} \sum_{a \in A} P_t^a(r) \tag{1}$$

For HoN (and most common MOBAs), it holds that $0 \leq P_t^a(r), K_t(r) \leq 9$ and $|A| = 10$. We studied the frequencies of the $K_t$ values for all replays in $r \in R$. Results (see Figure 3) show that 90% of the times the AoI population value is below 2, while it is rarely ($< 5\%$ of the times) larger than 3. This suggests a low degree of connections between players who usually move in groups of two or less.

To further study the relevance of the AoI population values we averaged the $K_t(r)$ from all the replays for each frame. This analysis has the objective to identify how the AoI population changes in the different phases of the game. We define the average of the $K_t(r)$ for all the replays as:

$$Z_t = \frac{1}{|R|} \sum_{r \in R} K_t(r) \tag{2}$$

In order for $Z_t$ to be meaningful, it is required that all the traces have the same length[5]. The reason is that traces with different length would have their game phases not aligned. Therefore, we normalized the observations reducing them to the same length by performing a linear interpolation to filling the missing points in the shorter traces, such that:

$$K_t = K_{t-1} + \frac{K_{t+1} - K_{t-1}}{2} \tag{3}$$

Figures 4 and 5 show the behaviour of $Z_t$ , and the number of lone avatars ($P = 0$) respectively. From the images, we can distinguish the phases that characterize a typical MOBA game, as discussed 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:

[5] The traces should have also the same number of avatars, which holds since we removed the games with less than 10 players.

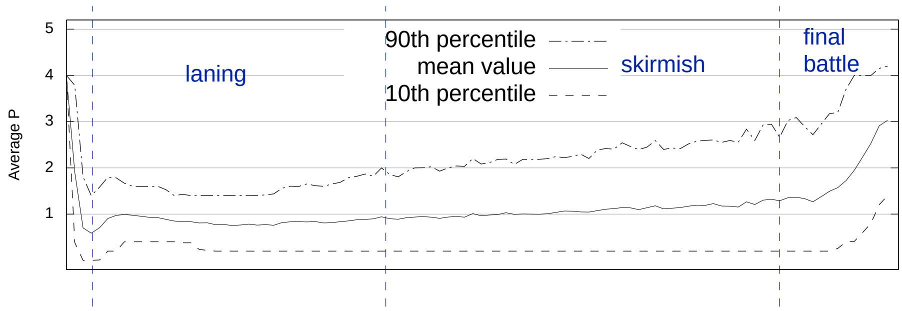



Fig. 4: Average AoI population over time

- *laning* (from the 3000th up to the 40000th 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 avatars travel alone.
- *skirmish* (from the 40000th frame up to the 90000th frame): this is the longest phase of the game, in which avatars coordinate in small groups to defeat opponent's structures at the hotspots or battle against other groups of avatars. In this phase we can observe a slow but steady increase of the average population with a consequent decrease of lone avatars.
- *final battle* (from the 90000th frame to the end): in the last phase, the majority of the avatars of both the teams aggregate in groups to battle for achieveingthe final objective. This phase is characterized by a drastic diminishing of lone avatars and a rapid growth of the AoI population.

In the following, we build from this outcome to better analyze the features relative to the AoI, such as its stability (Section 5.2) and the composition of the AoI between friends and enemies (Section 5.3).

### 5.2 AoI stability

The purpose of studying the AoI population stability is to understand for how long AoI population values remains constant without changing, and identify the most constant values. This analysis is different from the one described in the previous section, because it takes into account a window of subsequent frames, whereas the other one considers each frame in isolation. We define the *Stability Interval* ($\Theta$) as

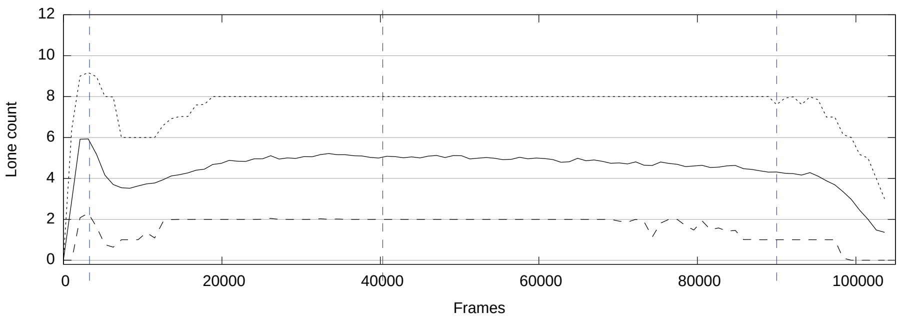


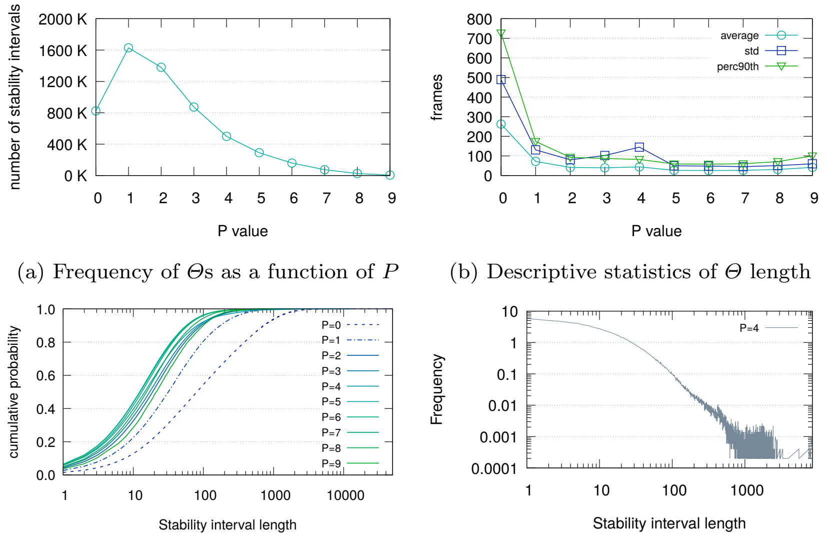

Fig. 5: Average AoI loneliness over time

the number of frames in which the value $P^a(r)$ ($P$ in the remaining of the section) remains constant. From the whole dataset we extracted all the $\Theta$ for each avatar $a$ in each replay $r$, creating a large list of pairs $(P, \Theta)$. For instance, a pair $(3, 76)$ means that an AoI has population of 3 for 76 frames in a row.

Figure 6 summarizes the results of the analysis. The frequency of different $\Theta$ as a function of $P$ (Figure 6a) shows that the most common $\Theta$ values lie in the interval $P = [0, 3]$. Figure 6b shows several descriptive statistics on the length of the $\Theta$. The average length is similar for all the $P$ values (between 50 and 80 frames), except for $P = 0$ that has an average of about 250 frames. The 90th percentile has a trend similar to the average, except for a greater distance between the average and the percentile in the observations for $P = 0$ (around 450 frames versus the 100 or lower of the other values). The standard deviation shows similar results to the 90th percentile, with a peak at $P = 4$. The cumulative distribution function of the length (Figure 6c) shows that $P = 0$ and 1 values have a larger amount of long $\Theta$ with respect to the other values.

From the interpretation of the observations we can draw the following considerations:

- $P = 0$ (lone avatars) is not the most common observed value, but presents the longest $\Theta$, meaning that this condition is quite stable during the game. This is confirmed by the observation of the $P$ frequency which count as more than 30% the total amount of cases in which $P = 0$ (see Figure 3).
- The *laning* phase described above is a relatively long phase of a typical MOBA game. In this phase the players typically form groups of two, which results in $P = 1$. This supports the observations in which $P = 1$ is the most common observed interval. By the nature of the laning phase however, $P = 1$ is not as stable as $P = 0$.




(a) Frequency of $\Theta$s as a function of $P$ (b) Descriptive statistics of $\Theta$ length

(c) Log-scale CDF of $\Theta$ length for all $P$ (d) Log-log plot of $\Theta$ lengths with $P = 4$

Fig. 6: AoI stability results

– $P = 4$ presents some peculiarities in the length of the relative $\Theta$, which are evident from the observation of the length standard deviation. By analysing the distribution of the $\Theta$ lengths with $P = 4$ (see Figure 6d), we can spot a higher number of observations in the tail, corresponding to long $\Theta$ intervals. By comparison, the distributions of the other values (not shown for reasons of space) present a much smoother curve, with less observations on the tail. This can be explained by the situation in which a whole team of 5 players ($P = 4$) move closer to each other toward a target, a possible situation in MOBA games, especially in the skirmish phase.

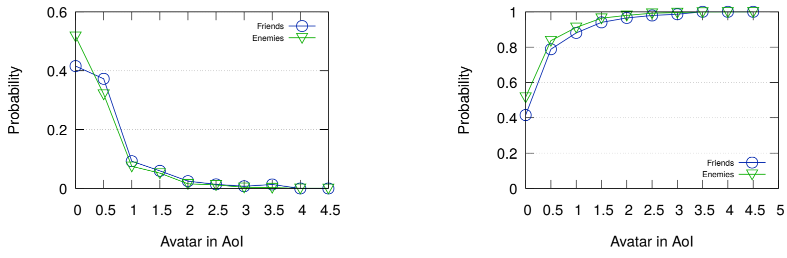
This analysis studies the AoI stability without differentiating whether the avatars in the AoI are member of the same or opposite team. Such difference is considered in the following section.

### 5.3 Friends and enemies in AoI

We examined the composition of the AoI in terms of number of player of the same or opposite teams (i.e. friends and enemies). We recall that $K_t(r)$ is the average AoI population value for a frame $t$ and a replay $r$ (Section 5.1). Here we define $FK_t(r)$ and $EK_t(r)$ respectively as the average number of friend and enemies in the AoI. Figure 7 shows the probability (left) and cumulative (right) distribution functions for the number of friends and enemies in the AoI.

From the interpretation of such data, it is possible to make the following considerations:

– half of the time the avatars have no enemies in their AoI and for the 40% of the time also no friends. In fact, when an enemy is in the AoI, it can represent




(a) Probability Distribution (b) Cumulative Distribution

Fig. 7: Number of friends and enemies in AoI

a threat. Instead, when a friend is in the AoI the reward for the actions in game are divided with it. For these reasons it is common that an avatar travel alone;

- 10% of the time avatars have an enemy and friend in the AoI. This suggests that it is more common to encounter just one enemy alone, in particular in the *laning* phase, and to travel with just one member of the team;
- for a small fraction of the time the number of enemies in the AoI is large representing the moments where team battles are performed;
- in general the amounts of friends and enemies in the AoI are quite similar. The reason could be that when an avatar meets an enemy it is very common that it is not alone but with some components of its team because it increases the possibilities to win the battles. This behaviour is observed the most in the skirmish phase.

Finally, we take one replay as representative candidate: Figure 8 represents the average number of friends (the top line) and enemies (the bottom line) in the AoI of the avatars during the match. From the figure it is possible to follow each

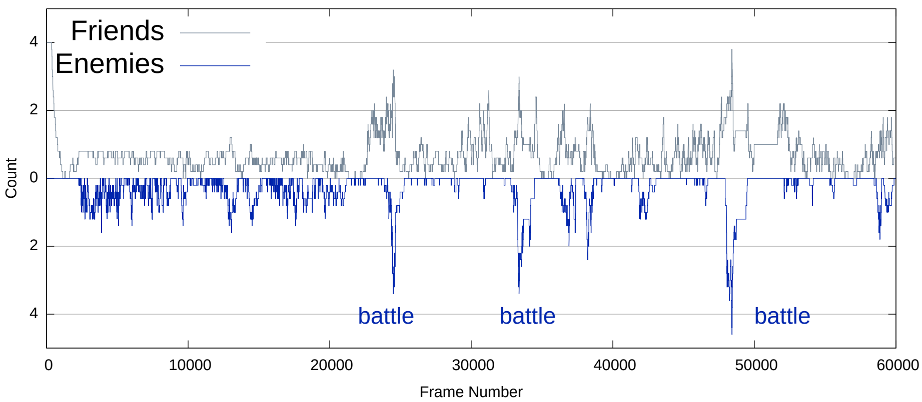



Fig. 8: Friends and enemies in AoI. The average number of friends is represented by the top line, whereas the enemies by the bottom line.

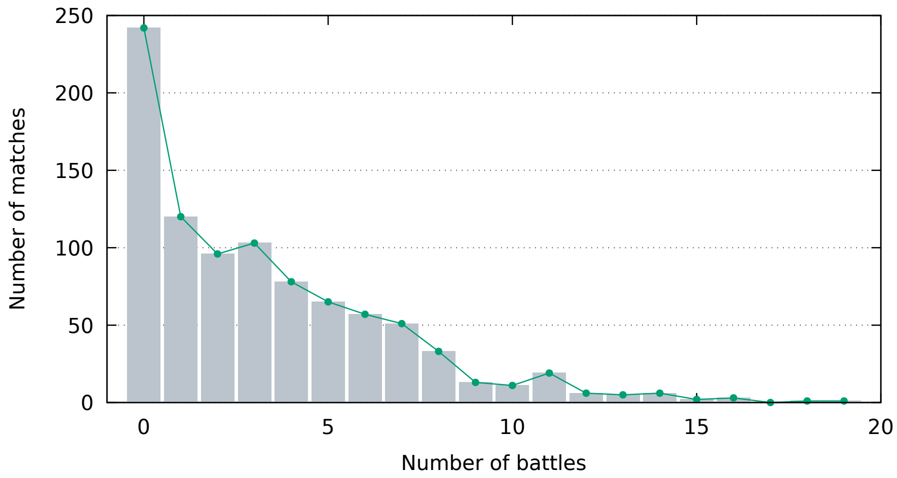



Fig. 9: The histogram shows the number of replays (y-axis) having the corresponding number of battles (x-axes)

of the phases of the game. At the very beginning each avatar has 4 friends and 0 enemy in its AoI. Next, around frame 20000, we have the *laning* phase where the number of friend and enemy in the AoI is similar. In this phase small battles are performed, and this results in having on average one enemy in the AoI. Next, there is the *skirmish* phase in which avatars coordinate in small groups to defeat opponent's structures. From the figure is evident how the number of friends in the AoI increases and the enemies are encountered in just 3 peaks. We can assess that the 3 peaks represents team battles, with all the avatars herded in a small area. In the specific replay, the *skirmish* phase ends before frame 50000. The *final battle* phase happens around frame 50000 where it has been performed the final 5 versus 5 battle to define the winner.

## 5.4 Number of Battles

From the analysis about the number of friends and enemies in the AoI presented in Section 5.3 we detected that it is possible to estimate the number of battles in a game by looking at the average number of enemies in the AoI of each of the avatar in a game. To count the number of battles we count the frames for which holds $EK_t(r) > 3$. These are the battles that involve the majority of the avatars in the game and decide the winner of the game. In order to avoid counting multiple times the same battle, when a battle is first detected we wait at least 100 frames before increasing again the counter. Figure 9 depicts the results we obtained analyzing all the replays. We found that the majority of the matches ended without a large battles (i.e. around 250 matches have 0 battles). This suggest that the victory can be achieved by smaller battles during the *skirmish* phase, without one or more large battles at the end. Also, battling in groups require all players of a team to have a relative high confidence in the game, which hinder the formation of groups when not experienced players control the avatars [17]. The largest part of the matches have from 1 to 5 large battles. It is interesting to note that exist a small number of the replays having more than 10 large battles; this can be the case when two teams have similar strength and take longer to win.

### 5.5 Hotspot analysis

Finally, it is important to understand if it is possible to detect hotspots described in Section 3 by analyzing the replays. In this section we analyze the amount of time spent in average by each avatar in the different position of the map in order to observe the most visited positions by avatars. To this end, we divided the map into a grid of $100 \times 100$ tiles, each tile having the same dimensions. For each trace, we counted the presence of avatars for each tile, and then averaged the count considering all traces. Figure 10 presents the heat map depicting for each tile the amount of avatars traveling in that specific portion of the map. From the figure we can detect mainly 6 hotspots in the following position in the map: (i) the two team bases, respectively the top right and bottom left corner; (ii) the three points where the avatars of opposing teams meet in the *laning* phase (the center of the map, the top left corner and the bottom right corner); (iii) one more hotspot correspond to the location of a special element that gives the team a significant advantage, therefore the surrounding area is usually patrolled by the teams.

It is interesting to note also that the majority of the trajectories of the avatars follow predetermined paths between the hotspots. This observation is important in terms of the design of a mobility model, because it allows to use direct paths from one hotspot to another. The same assumption was also made from other mobility models in other games, such as Blue Banana [24] for Second Life.

## 6 Conclusion

In this paper we analyzed the spatial features of avatar movements in a MOBA. We used real movement traces of Heroes of Newerth game, a popular MOBA game. A subset of the dataset we used in this analysis is publicly available [10]. The analysis of real traces allowed us to observe several features of a MOBA game: (i) the identification of the different phases of a match and how the avatars behave in the different situations, (ii) the detection of the number of battles in the match and in which phase the battles happen, and (iii) the hotspots of the map representing the main crowded areas of the game. The ultimate aim of this paper is to provide insights about avatars movements, in order to help creating mobility models for a MOBA game. These are the key findings of our analysis:

– in about 81% of the frames, an avatar has 3 or less other avatars in its AoI. This value is smaller at the start and larger at the end of the game, when the largest battles occur. Often, avatars wander alone;
– in 90% of the cases, there is a change in the number of avatars in AoI in less than 100 frames, with the average being from 50 to 80 frames depending on the AoI size. This confirms the fast-paced nature of the game;

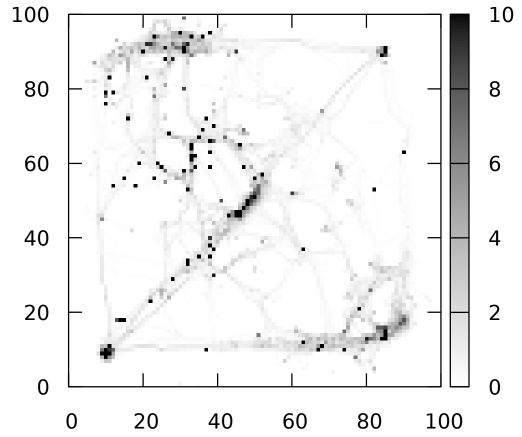



Fig. 10: Hotspot analysis. The heat map represents the average avatar population presence in each tile

– the number of friends and enemies in an avatar's AoI is related: generally, the number of friends and enemies is very similar throughout the whole the game;
– in about 27% of the analyzed replays we have found no large battles, suggesting that they are less likely to happen than one might initially think.

As a future work we plan to extend the analysis and develop a mobility model with the help of machine learning techniques. Such model can be specialized for the different phases of the game and also the different typologies of heroes in the game. Also, this methodology can be exploited to analyze different traces and different game genres. Finally, the presented analysis can serve to other current research topics connected to MOBAs, such as the creation of AI agents that play MOBA games [28], and the inference of the level of ability of MOBA players by the analysis of their movements [15].

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