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► **To cite this version:**

Alexis Mortelier, François Rioult. Addressing the Complexity of MOBA Games through Simple Geometric Clues. 14th International Conference on Computational Collective Intelligence (ICCCI) - 2022, Sep 2022, Hammamet, Tunisia. hal-03784769

HAL Id: hal-03784769

<https://hal.science/hal-03784769v1>

Submitted on 23 Sep 2022

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Addressing the Complexity of MOBA Games through Simple Geometric Clues

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Abstract. Recently, the analysis of e-sport data has particularly attracted the attention of machine learning researchers. We contribute here by proposing, on the MOBA (Multiplayer Online Battle Arena) game *DotA2* (Defense of the Ancients 2), an analysis of the relevance of geometric clues relating to the behavior of the players. The geometric clues we have chosen concern the trajectories of the players and the characteristics of the polygon described by the players of a team. More precisely, for the polygon clues, we computed, for each second of the game: the convex area, the diameter, the grouping capacity (average of the distances to the barycenter), the inertia (second order moment of the distances to the barycenter) and finally the distance to the opponent's fortress. During a regression on the number of alive heroes, the learning performance of an RNN (precisely a LSTM) fed by our simple clues allowed us to evaluate their relevance in describing this complex game.

Keywords: trajectory analysis, MOBA games, important moments highlighting, RNN

1 Introduction

Context Electronic sport or e-sport consists of the competitive playing of video games. This activity provides numerous traces that data science researchers like to study. Indeed, these researchers are often gamer themselves so they are familiar with the subject of their study. Moreover, e-sport has emerged as a serious discipline, operating in a similar way to sport, with the arrival of classic clubs such as Paris SG, AS Monaco, AS Roma and FC Grenoble. This craze is reflected in the particularly attractive financial amounts (up to millions of dollars) offered to the teams participating in the tournaments. For example, in 2018, The International 2018 tournament allowed the first 18 teams to share more than 25 millions Dollars (40 millions this year).

E-sport is a boon for data science research because activity traces are easily and massively available. Unlike traditional sports where it is difficult to obtain accurate data, each e-sport game is archived on servers in a very precisely exploitable format. The interest of e-sport also lies in the expression of human and collective organizations, for example the tactics and strategy of a team of players, which are comparable to those implemented in real sport.

Motivations Our main motivation is to analyze MOBA games (Multiplayer Online Battle Arena games) in order to better understand the performance of the best teams. This understanding would allow us to explain the reasons for the failure or success of a team and would provide means of analysis for the games. These means could then be used to automatically produce game summaries by characterizing highlights.

However, MOBA games are particularly complex to analyze: each player can choose his avatar from among a hundred, each avatar can cast four exclusive spells and improve his skills (movement speed, attack frequency, armor, mana regeneration, etc.) thanks to six items of equipment to be chosen from among a hundred. It is therefore desirable to reduce this complexity.

We believe that the spatial organization of the players is crucial for analyzing performance in these games and that it is not necessary to examine all the minute details of a game to characterize its important moments. Moreover, MOBA games are team games and the study of spatial organization allows us to focus attention on the collective aspects rather than on individual details.

Position Compared to other works in the field, our proposal presents two originalities. Firstly, we focused our study on the *collective* character of the practice of a MOBA, because it is fundamentally a team game emphasizing group actions to the detriment of individual ones [3]. To do so, we compared the relevance of clues related to the individual position of the players on the field and the geometry of the collective organization. We are looking for simple clues to calculate and exploit and we do not wish to focus our attention on individual behaviors and characteristics (equipment, skill tree).

We therefore compared the contribution to a learning method of the individual trajectories of the heroes *versus* the geometric measurements on the polygon described by the players (area, diameter, distance to the objective, etc.). This approach is qualified as *wrapper* in [4]: the relevance of a descriptor is measured by its contribution to the classification or regression model, it is a method of feature selection.

Secondly, we have decided to work only on data from games played by e-sport professionals, grouped in renowned teams. We wanted to study games performed by players who are used to play together and producing a high level of performance. This position is original in the literature [5,3]. In order to privilege quality over quantity, we did not wish to study millions or even billions of games [2]. Indeed, the matchmaking of occasional players is based on their expectation of winning, which leads to the constitution of balanced teams.

2 Related work

Due to the lack of space in this short version, this section is available on the extended version of this article at this address¹.

¹ https://hal.archives-ouvertes.fr/hal-03699200/file/Addressing_the_Complexity_of_MOBA_Games_through_Simple_Geometric_Clues.pdf

3 Addressing the complexity through geometric clues

DotA2 is a team game where coordinated and synchronized movements are paramount, independently of individual behavior. We believe (as [2]) and show here that geometric clues from player trajectories are sufficient to reveal the complexity of this game. Considering these geometric clues alone rather than examining individual player behaviors in terms of inventory and skill tree allowed us to propose a generic approach for the MOBA genre and to work on the basis of simple hypotheses.

We therefore compared the relevance of three types of geometric or positional clues: (i) player trajectories, (ii) trajectories *enriched* by the coordinates of the hero's orientation vector (this data is simply provided by the game engine) and (iii) the characteristics of the polygon described by all the players of a team. We normalized the data provided by the game engine so as to obtain one measurement per second of game time.

We considered that a game is divided into three major phases of play : the early-game, the first 15 minutes during which the heroes are weak and seek to obtain gold and experience to gain power. It is during this phase that ambushes are attempted to gain an advantage and ruin the opponent's progress; the mid-game (from 16 to 35mn), some heroes are powerful enough to make team fights possible; the late-game: (36mn and beyond), the heroes have their maximum power and no longer seek to collect gold or experience: towers and the enemy fortress becomes the only objective.

DotA2 provides traces of game activities in the form of a *replay* file that can be retrieved after each game. The 258 games we analyzed were those of a major tournament of the game, The International 2018². Our goal was to determine clues, characteristic of the spatial organization of the players. Highlights occur approximately every three minutes and correspond to the confrontations of the players giving rise to the disappearance of some (virtual *death* followed by a resurrection after a variable time). In order to obtain results that are sufficiently general and do not depend on the intrinsic complexity of the game, we focused our attention on geometric clues linked to the positions of the heroes.

3.1 Wrapper Approach with RNN

We used a *wrapper* approach [4] which assumes that the relevance of a feature is related to its capacity to improve the quality of learning. Unlike the *filter* approach, more common in statistics, which attempts to evaluate the credit of features from the data alone, the wrapper approach attempts to identify the best subset of features to use with a learning algorithm. We used this approach to compare the suitability of trajectories with that of polygon features by examining the performance obtained by models computed on these clues.

The learning algorithm we used was a Long Short Term Memory (LSTM), a particular recurrent neural network (RNN) [6] architecture. RNNs are designed

² see <https://www.dota2.com/esports/ti10> for this year's edition

to handle temporally evolving data: if a cell computes an output signal from the inputs, it additionally transmits a hidden state to the next cell, that influences it. The cells of an LSTM additionally include a memory/forget mechanism that solves the problem of vanishing gradient.

The LSTM was here well adapted to our goal which was the study of a long game (35 to 50mn x 60 measures/mn). The target was the number of players alive 5 seconds into the future (as recommended by [1]), because the position of a dead hero was conventionally frozen at the place of its death, and then it was reborn at the fortress position. If this time lag was not introduced, the LSTM could use this information and introduce a bias in the results.

The results we report in the next section were obtained on a single-layer LSTM with 128 cells, which allowed us to best assess the difference in relevance between our choices of clues. However, adding additional layers allowed the network to acquire a universal approximator behavior and thus, fed by the trajectories, to potentially capture the expressive power of the geometric clues of the polygon. The experiments we have carried out in this sense show that the more layers we added, the less noticeable the differences between the types of clues (see Figure 3) .

Finally, we performed a Student’s t test to check whether there was a significant difference in relevance between the use of trajectories, enriched trajectories or polygon clues. The Student test calculates a value between two distributions called p -value. If the score is less than 0.05, then the hypothesis that the means are equal can be rejected.

3.2 Experimental conditions

In the experiments whose results are presented in the next section, we fed an LSTM with either player coordinates or polygon geometric clues and evaluated the relative relevance of these attributes by examining the MSE. The objective function was the number of living heroes in each team (from 0 to 5). We considered that the LSTM worked in *regression* because it had to predict two continuous quantities on the interval $[0, 5]$. Figure 1 shows a schematic of our training process.

During our experiments, we also considered two types of chronology for the LSTM inputs:

learning since the beginning of the game phase: the LSTM was fed *continuously* by a single sequence, with data between instants 0 and t and predicted a value at $t + 5$;

sliding window learning: the LSTM was fed with multiple sequences from $t - w$ to t and predicted at $t + 5$, for w a window width that we let vary between 5 and 120s.

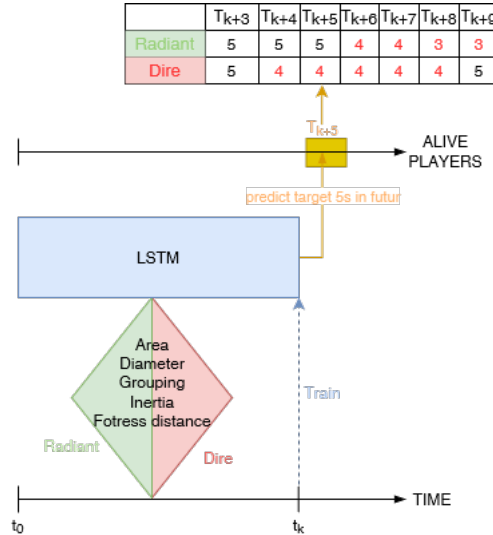


Fig. 1. LSTM training scheme on the continuity of the game.

4 Results

4.1 Learning since the beginning

Figure 2 represents the MSE boxplots, for each phase of the game. It can be observed that, independently of the phase, the polygon clues allowed a better prediction: the median of the MSE is the lowest and the dispersion is less important. Table 1 provides the values of the corresponding Student’s tests: when the cell has a green background, the means are not equal.

Phase	Poly vs traj	Poly vs enriched traj	Enriched traj vs traj
Early	2.989.10 ⁻⁶	1.104.10 ⁻¹⁰	0.113
Mid	1.121.10 ⁻¹¹	4.633.10 ⁻¹³	0.782
Late	4.366.10 ⁻⁹	1.761.10 ⁻¹⁶	4.043.10 ⁻⁵

Table 1. P-values of Student test for regression.

During the early and middle of the game, the trajectories induced a slightly lower median error than the enriched trajectories, but the dispersion for the enriched trajectories is lower. For the end of the game, the results were more marked, the dispersion increased for the three types of clues and there were many more outliers. This could be explained by the fact that at the end of the game the virtual deaths are much more punitive (their duration depends linearly on the level of the player, maximum at this period). When a collective behavior led

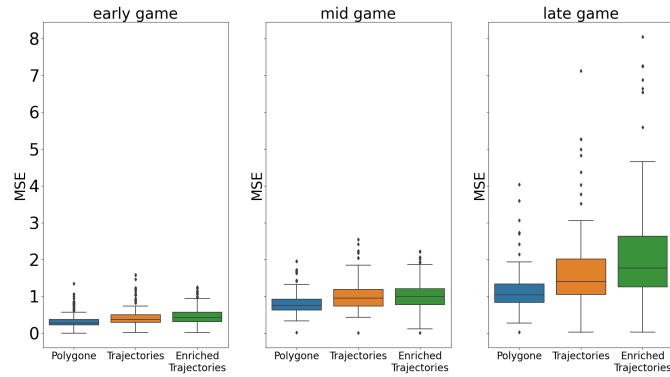


Fig. 2. Distribution of the MSE over the continuity of the game in regression.

to an important moment, the model detected it, however the players were more cautious because of the stake and canceled their action at the last moment.

Figure 3 shows the evolution of the relevance when increasing the number of layers of the LSTM (each one has 128 cells). Although the polygon clues were still the most relevant, there was a convergence of the three types of clues when the number of layers increased. However, the addition of layers had a significant algorithmic cost, particularly in terms of the number of epochs.

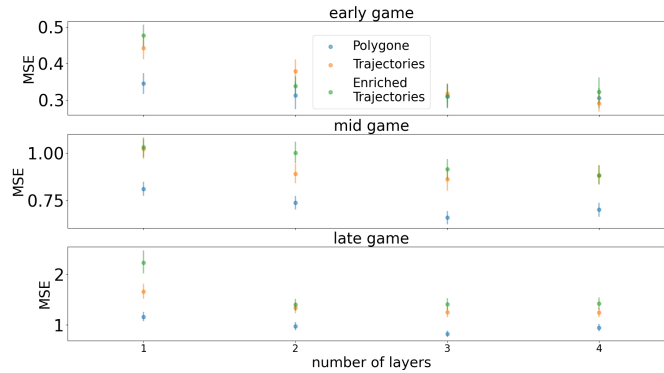


Fig. 3. Evolution of the MSE according to the number of layers for the regression.

Finally, the polygons were the most relevant geometric clues for the regression problem, regardless of the game phase, both from an evaluation and computational time perspective. We also found that the LSTM converged faster when fed by the polygon clues rather than the trajectories.

4.2 Sliding window learning

When using sliding windows, the performance of the different types of clues, depending on the width of the window. Switching to sliding windows greatly improved the results obtained with the clues on the trajectories, equally for the trajectories and the enriched trajectories. The performance of the clues on the polygon was much poorer, and using sliding windows did not allow them to be sufficiently highlighted. These clues need to be taken into account for the entire period to reveal their potential relevance.

5 Conclusion

Using an LSTM that predicted the number of living heroes, we have shown that it was possible, by valuing geometric clues about the players' positions, to draw attention to important moments in a *DotA2* game. Although *DotA2* is a complex game, there is a strong relationship between simple positional clues and the occurrence of important moments.

Among the examined clues (geometry of the polygon described by the heroes, trajectories and trajectories enriched by orientations), those on the polygon proved to be more relevant for all phases, but it was necessary to learn on the continuity of the game. When using windows of variable size, the trajectories relatively gave better results but did not reach the performance of the polygon on the continuity of the game.

We have also found that increasing the number of layers in the LSTM allowed it to behave as a universal approximator: the more layers, the less sensitive the differences in performance between the feature types, although trajectories still required more learning epochs. The polygon clues, with the development of a small amount of preliminary computation, thus allowed for a reduction in the computation required for learning.

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