Assessment of Video Games Players and Teams Behaviour via Sensing and Heterogeneous Data Analysis: Deployment at an eSports Tournament

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Abstract. eSports is video gaming where individual players or teams oppose their physical, psychological and emotional conditions in the game context to achieve a specific goal by the end of the game. However, neither players nor teams have been studied in real scenarios. In this paper, we report on the deployment of sensing system for collecting a player biometric data (a computer mouse and keyboard), voice data, and heart rate in an eSports 'Team Fortress 2' tournament. Upon the data analysis we demonstrate that an increased heart rate has a negative impact on the player performance. At the same time, successful teams communicate more during the game. Moreover, team communication in positive tone has a positive contribution in the overall team performance.

Keywords: eSports · Intelligent sensing · Data analysis · Deployment

1 Introduction

eSports is a quickly developing area of video gaming where individuals or teams compete within a game environment for achieving a specific goal by the end of the game. Currently, eSports audience involves around 1.5 billions players worldwide [1], eSports is recognized as sport in many countries, lots of local and international tournaments are regularly organized and followed by visitors and via online broadcasts or streams. By playing games, the eSports players are involved in continuously changing context where they have to take decisions quickly. It results in stress situations during the games which influence their psychological and emotional conditions. At the same time, eSports specific injuries could be identified in advance and therefore avoided. Performance of individual players and teams depends on these factors drastically.

However, eSports players have not been studied in real conditions. From the research point of view eSports is in its infancy and is limited within in-game

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data analysis or modelling players [25]. Although myriads of research works have been published on the data collection in sport [9], finding correlation between the stress/fatigue and physiological parameters [7], identification of specific movement pattern [15] they still have not been adapted to the eSports domain. This domain is quite specific in terms of decision taking in a short period of time, constantly changing game context, stress environment. Moreover, there is a lack of eSports deployments which could help for data collection in real scenarios and further data analysis. Indeed, the deployment related studies allow for testing particular testbeds, technologies, and getting feedback on proposed research ideas in terms of their practical feasibility [3,19].

The problem of players assessment and their behavior analysis has been approached theoretically and in lab conditions from (i) psychological point of view and (ii) physiological point of view when a certain dataset was collected using various sensors fixed on the player.

Regarding psychology, there is a bunch of works combining the studies on both psychological self-reports from players and log files based on the in-game events are generated into a meta-synthesis player types profile [11]. Another research direction deals with the general psychological motivation of human to play digital games [10]. Relevant data-driven approaches aiming at a player modeling were discussed in [14]. The authors emphasize a variety of machine learning methods applied to the analysis of in-game actions of player behavior. Also, there is a study combining both psychological and physiological assessment of players in terms of their reaction time. It is assessed through the gaze tracking and personality traits [17]. While combining both psychological and physiological methods is promising, there is still a lack of this research since it requires truly multidisciplinary research team.

As for the physiology related research in eSports, a number of sensing technologies have been used so far. We note here that for physiological data collection unobtrusive sensing technologies are welcome by professional players who a highly sensitive to any kind of discomfort during the game and training routine. Unobtrusive technologies include the usage of keyboard and computer mouse during the data collection, an eye tracker placed on top or below a display [24], a gaming chair equipped with the sensors [22] as well as the video game recordings (demo files) [21] collected during the game. As noticed earlier, some sensing technologies, e.g. wearable sensing technologies, may cause unpleasant experience for the players. This kind of discomfort may result in the performance reduction. An Electroencephalography (EEG) headset [8], a heart rate sensor and wearables [13] is a typical source of discomfort for the players. At the same time, using some sensing technologies, e.g. EEG, it is a non-trivial task to collect high quality data. EEG measurements are characterized by a number of artefacts heavily influencing the measurements quality. As a result, the gaze tracking is among the popular research trends in eSports. In [4,16] the authors studied the differences between an amateur and Pro players using an eye tracker and the data collected from the computer keyboard and mouse. As a result, the authors demonstrated the patterns of gaze information from the players with different experience level.

The players behaviour can be assessed using the movement related sensors integrated in a gaming chair [22]. Feature engineering and machine learning have helped identify specific features describing the players with different level. It is worth noting that the research reported in [16,22] involved the data collection from professional players in lab conditions. As noticed earlier, the eSports related deployments, e.g. data collection and players assessment in real conditions, are missing so far.

In this work, we report on a sensor network deployment at an eSports tournament. The goal of this deployment is to collect the eSports data including game events (computer keyboard, mouse), voice (microphone), heart bit (wireless heart rate monitor) for assessing the players and teams behaviour in real conditions. To the best of our knowledge, it is the first deployment at an eSports tournament. The results obtained in this work are essential for both eSports players and researchers - they demonstrate which data are relevant for analysis and how the team and players can develop their professional qualities, communication in the team, and control certain physiological parameters. Moreover, this study is highly important in the situations when the eSports team formation is in progress [6] and for the analysis of the professional eSports athletes' work [20].

The paper is organized as follows: we present the eSports deployment in Sect. 2 where we provide the details on the tournament, game discipline, sensing system, and the data collection procedure. We then demonstrate the analysis of collected data in Sect. 3 by focusing on our results in voice, heart rate and game events analysis. Finally, we provide concluding remarks and discuss our future work in Sect. 4.

2 Deployment

Prior to dig deeper into details of the deployment scenario and the sensor network used for data collection, we stress the point that this deployment was carried out at a tournament in real conditions. It means that this event was featured by the tight schedule, there were real participants, and a reasonable prize pool. That is why (i) the deployment preparation must be perfectly organized, (ii) there must be the data backup system, and (iii) the entire deployment and each single sensor must be unobtrusive for the players as it may have a negative impact on their performance.

2.1 Scenario

Tournament. Moscow LAN is the annual Team Fortress 2 (TF2) tournament which helds in Moscow, Russia. 2020 tournament was cancelled due to Covid-19 pandemic. 7 teams participated in 2019 TF2 Moscow LAN tournament[1]. The tournament lasted for 2 d at Winstrike Arena: the qualify stage in the first day and the quarter-final with the grand final during the second day. 7 teams double

[1] TF2 Moscow LAN official website https://match.tf/tournaments/44.

elimination bracket was used for the qualify stage. During the tournament an online stream on Twitch platform was organized. Heart rate monitors performing the team captains heart bits were also streamed as an overlay and were always visible to the Twitch streamers (Fig. 1).

Fig. 1. TF2 Moscow LAN 2019.

Competitive play in TF2 refers to the organized gaming according to Highlander – a standard competitive format shared by the majority of leagues. This set of rules assumes that the game should be played in a prescribed list of maps and regimes (King of the Hill, Payload, Capture Point, Timed Capture the Flag) with some disabled options (critical hits, damage spread, and customization). Most players that follow the standard competitive format use the standard competitive lineup made up of the following game classes (Medic, Demoman, Pocket, Roamer, and Utilities). Therefore each team at the tournament is composed of 5 players in total leaded by their captain.

Game. TF2 is a First Person team-based online multiplayer game available on the PC and other platforms[2]. It is one of oldest games on Steam with intriguing concept and small, but passionate competitive community. The original version

[2] C.Moore 'Hats of affect: A study of Affect, Achievements and Hats in Team Fortress 2', available at http://gamestudies.org/1101/articles/moore.

of this game was a modification (mod) of Quake made by id Software in 1996 and reworked by Valve. It became highly popular among gamers seeking the alternative options from the individualistic deathmatch style of play that dominated early multiplayer FPS games.

Players of two teams respawn near their fortresses after loosing all their character hitpoints. Each player belongs to the nine different player classes which are divided into three categories: assault, defence and support. The tactical combinations of these classes produce a complex formulae for matching different elements in different sequences. Effective communication and coordination, synergy between the players, accomplishment of their character abilities make the teamwork the most important aspect for winning.

The core of combat system is the rules of interaction between nine different classes divided by Valve in three categories: offense, defense, and support. Each class has the unique attributes that determine its strengths and weakness: health, movement speed, weaponry, and other innate abilities such as health regeneration or the ability to Double Jump.

2.2 Hardware and Sensor Network

The tournament infrastructure included 40 high performance PCs connected through 1 Gbps local network were used during TF2 Moscow LAN tournament. 35 PCs were occupied by the eSports players, 1 PS was used for game hosting, 2 PCs were used for Twitch online-stream and 2 PCs were in hot reserve. One additional computer (Intel NUC) was used as a FTP and NTP server. Custom made data collection software was used on every gaming PC. This software enable recording of keyboard pressings, mouse movements, microphone sound capture during the game sessions. At server PC full log was enabled for all the in-game events. Wireless sensor network was used for heart-rate data collection. The captain of each team was equipped with a HRM belt connected to Raspberry PI SBC. Heart-rate was measured by HRM belt. Raspberry PI captured signal from the local HRM belt, decoded it and than transferred to Twitch stream PC. The PC used for online-streaming was featured by a specific software effectuating the hear-rate data visualisation and video overlay software (Fig. 2).

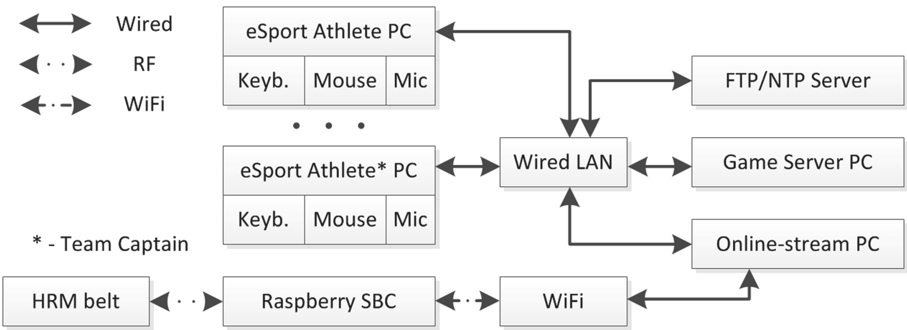

Fig. 2. Block diagram of sensor network for eSports data collection.

It should be noted that our aim was to ensure unobtrusive sensing and avoid potential situations where the sensors could disturb the players or create any kind of interference to gaming procedure in the scope of tournament. That is why we had to give up on the idea to use as much sensing technologies as we have tested earlier in the lab conditions [22,23].

2.3 Data Collection

All the gaming PCs and the game server were synchronized with accuracy up to 10 ms. To do this special software settings were applied and the dedicated NTP server was used [23]. Data collection software performs continuous recording of keyboard, mouse and voice during the course of tournament. Players were able to switch the PC to another one between the tournament stages. The game server performs the full logging of in-game events including IP addresses of each connected player and his player-id and nickname. These allows us to cut the continuous recorded timeseries to the chunks correlated with the particular game and particular player. Due to time synchronization across all the computers different timeseries were synchronized and ready for the analysis.

We note here that our future plans include the collection and analysis of game recording (video) files. This activity requires extra efforts in improving the experimental testbed by adding data center facility [5].

3 Data Analysis

In terms of data analysis, a few months before the deployment we have discussed with the TF2 players and managers the metrics of interest for this particular discipline. It appeared that the motor skills could be developed, i.e. trained, and are not that important for the team performance. As for the heart rate, most of the players were aware of the point that it does have an impact on the performance and can be controlled using specific techniques. At the same time, the team speak, i.e. communication in the team during the game, is much more important in terms of the overall team performance and requires research efforts.

3.1 Game Events

Along with modern biometric indicators, the logs of in-game events remain a significant part of the analysis. In this study, we performed the analysis of the movements and rotations of players' avatars using the data of their 'virtual' behavior. One of the issues was about association of virtual and real world: if the motion intensities can characterize the team or a certain player, how these characteristics depend on the map, the level of the opponent team and whether the match is final or it is still qualification. The intensities for yaw and distance were calculated as the sum of their absolute changes per second.

As shown in Fig. 3a, the intensity of player's avatar rotation is more a characteristic of a player or his/her role in the game because within-player differences

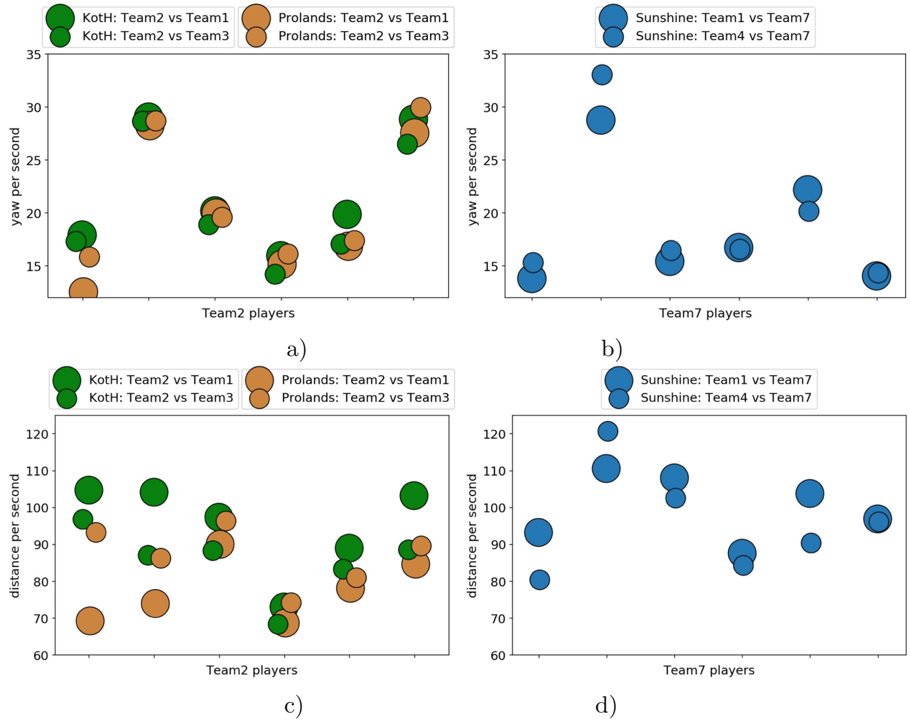

Fig. 3. a) and c) - respectively, the yaw and movement velocities for Team2 players in two matches with Team1 (the match in grand final with the winner) and in two matches with Team3 (also strong team) on two different maps: *KotH* and *Prolands*; b) and d) - respectively, the yaw and the movement velocity for the players of Team7 (has hot won any match) with Team1 and Team4 (has not played in final) on the map *Sunshine*.

look smaller than the between-player differences for two maps and matches versus two different teams. This remains true also for Team7 that did not win any match: rotation intensities do not depend on the opponent teams significantly, although Team1 and Team4 have different professional levels (see Fig. 3b).

However, the velocity of the avatar movement demonstrates significant differences with respect to the map (see Fig. 3c). Interestingly that all the players of Team2 demonstrated higher intensities for both yaw and distance for the map *KotH* than for the map *Prolands* in the matches with the champion Team1. The velocity of the movement also depends on the opponent team and this is different for different maps (see Fig. 3c).

Although both movement and rotation velocities depend on the opponent team, their average values over the team players do not depend significantly on the team level: the values for Team7 (see Fig. 3b and Fig. 3d) are comparable with the values for Team2 (see Fig. 3a and Fig. 3c, respectively).

3.2 Heart Rate

To qualify for the final of the tournament, there were two competing teams Team3 and Team1. As expected, the fight turned out to be hot. This can be judged not only by the fact that the battle was long, but also according to how the heart rate of the team captains changed. With each new map, the stress and pressure were growing. Figure 4 shows the heart rate range (bits per minute) of the team captains on three different maps. Upon reaching the score 1 : 1 on the maps, the captain of the blue team (Team3) was stressed enough. On the last map, his average heart rate increased by as much as 25 bits/min and reached a record 135 bits/min. At the same time, the captain of the red team (Team1) was much calmer. Playing at a heart rate of about 125 bits/min on the second and the third maps, he made a significant contribution to team play. We tend to think, it was his deadly concentration in the game that brought the team to the final of the tournament.

In the final game, the situation is different. Team2 captain was in constant pressure throughout the game. Team1 captain, on the other hand, was clearly relaxed in the first two rounds, having the heart rate 20–30 bits per minute lower. The situation changed when, with the score 1 : 1 on the maps, the control stage of the game for winning the final began. The average heart rate of team1 captain increased by 10–15 bits and nearly reached the heart rate of his opponent captain. However, in such a stressful situation, it was team1 which won the tournament. Here, the skillful sniper of the winning team also made an invaluable contribution to win the game.

3.3 Voice

To analyse players' communication during the game, we automatically labeled the emotions for every players' voice record. This was done by training a machine learning emotions classifier on a publicly available dataset and applying it to the collected dataset for recognising emotions.

As the base classification model, we used Random Forest classifier [2] trained on Mel Frequency Cepstral Coefficient features (MFCC, see [12]). These coefficients are extracted from each 3 s interval (with time period 0.5 s) of each recording, so each interval is a training/testing object. We used 40 MFC coefficients.

To train Random Forest for emotions classification, we used publicly available Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) [18]. Originally, the database consists of >1000 recordings for 24 actors with 8 types of emotions: neutral, calm, happy, sad, angry, fearful, disgust, surprised. In our case, it is not reasonable to discern 'neutral', 'calm' and 'sad' classes in eSports audio data: all these emotions represent some kind of passivity. Empirically, we also noted that 'disgust' and 'surprised' classes turned to be not typical for considered tournament's audio. Thus, for the reason of classifier training we considered only the most representative classes: 'calm', 'happy', 'angry', 'fearful'. To make classifier robust, we also artificially (manually) collected 30 crops of

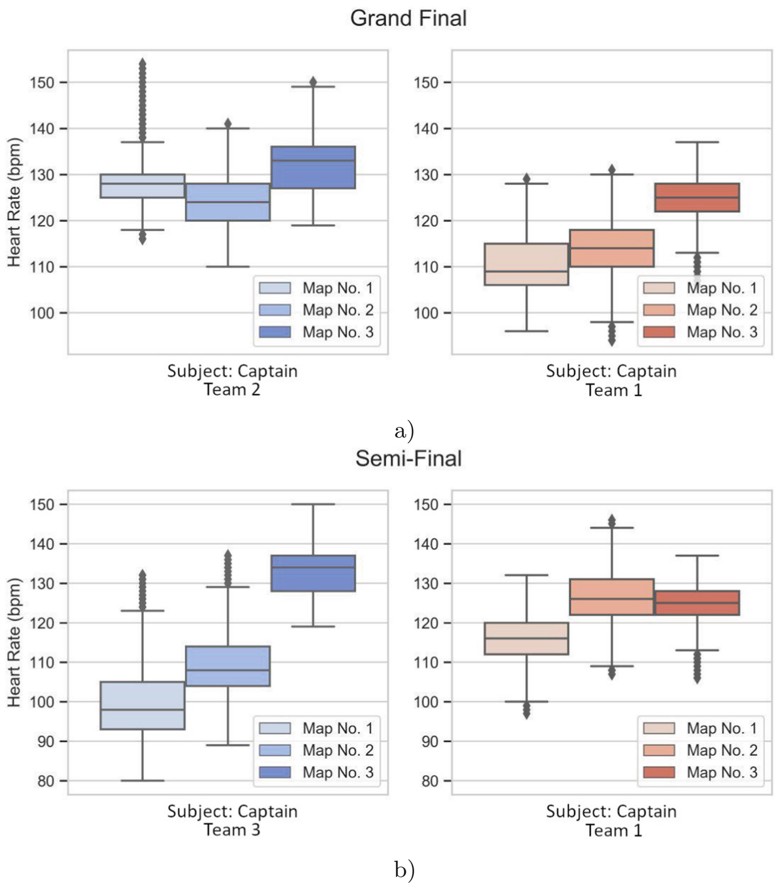

Fig. 4. Heart rate of team captains during a) final game, and b) semi-final game.

background sound from the tournament's audio dataset and added them to the train set with an artificial label 'background noise'. The final trained classifier provided 92.7% balanced accuracy score for 5-class classification on the 3-fold cross validation on the extended RAVDESS dataset.

We applied the obtained emotion classifier (MLP) to our eSports dataset, i.e. classified emotions of each player for every 3 s interval of the dataset. We define the player's **emotional passivity level** as follows.

$$\mathrm{EP} = \frac{\text{Calm + Background Noise duration}}{\text{Game duration}} \tag{1}$$

It is the fraction of time when the player was calm during the game. In the same way, we define the fraction of time when a player was 'happy' as follows.

$$\mathrm{PT} = \frac{\text{Positive tone's duration ('happy')}}{\text{Game duration}} \tag{2}$$

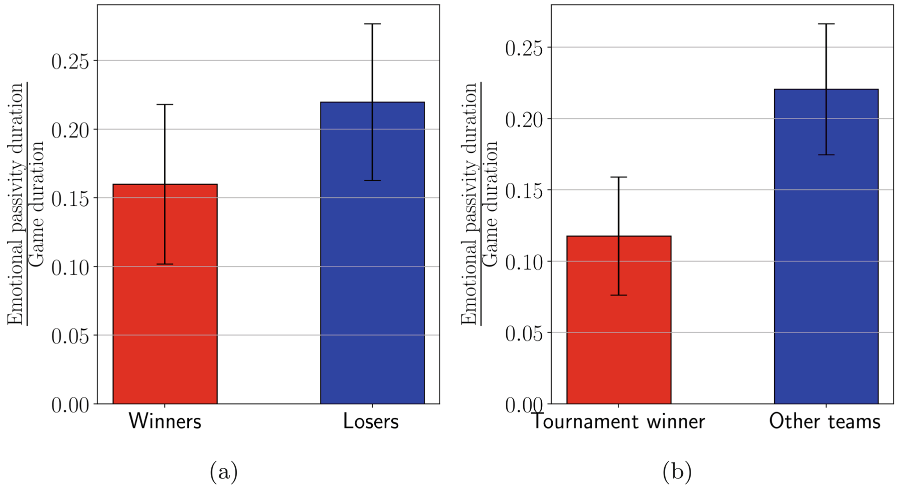

Fig. 5. Emotional passivity level for a) all winners vs all losers, b) the winner of the tournament vs all the others.

It is the fraction of time when a player was ‘sad’ by

$$\mathrm{NT} = \frac{\text{Negative tone's duration ('angry')}}{\text{Game duration}} \tag{3}$$

We depict the average values (averaged over the players in teams and over the matches) of EP, PT, NT for both winning and losing team in Figs. 5 and 6.

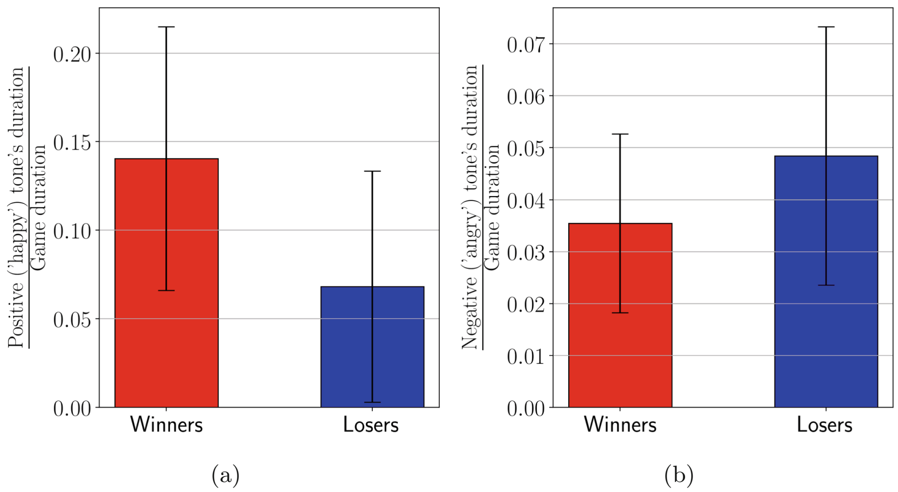

Fig. 6. Comparison of emotional tone of teams’ conversations a) positive tone, b) negative tone.

From Figs. 5 and 6 we extract the following insights:

– More successful teams communicate more;
– The communication of more successful teams is in a more positive tone.

Both observations have reasonable explanations: the proper team communication improves chances to win, and winning improves team's morale, providing more positive communication tone.

4 Conclusions

eSports research is a developing area lacking the players assessment in real conditions. In this work, we have reported on a deployment of sensing system at a real tournament followed by the data analysis. We have ensured the data collection from the computer keyboard and mouse, microphone, and heart rate sensor for performing the analysis of game events, heart rate and voice, respectively. These sensors were used intentionally for guarantying unobtrusive sensing during the competition.

Our results have demonstrated that rotation velocities depend on the opponent rather on the current team skill level. Also, our next finding (a reasonably straightforward one) was connected with the heart rate of the players (we assume here that all the players are equally healthy) - those players who managed to control their heart bit had success in their games. As for the voice communication, i.e. team speak, we came to two conclusions: (i) successful teams naturally speak more during the game, and (ii) the communication of successful teams is in positive tone.

As for the future work, we plan to add a data center facility for storing and performing the analysis of game video recording (demo files) as well as involve extra sensors, e.g. an eye tracker, the sensors for environmental monitoring, which ensure both unobtrusive sensing and provide more insights for the data analysis and making consequent inference on the players behavior and their performance.

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