Team ORG @ GameStory Task 2018

Mathias Lux¹, Michael Riegler^{2,3}, Duc-Tien Dang-Nguyen⁴, Marcus Larson⁵, Martin Potthast⁶, and Pål Halvorsen^{2,3}

¹Alpen-Adria-Universität Klagenfurt, Austria; ²SimulaMet, Norway; ³University of Oslo, Norway; ⁴University of Bergen, Norway; ⁵ZNIPE.TV; ⁶Universität Leipzig, Germany mlux@itec.aau.at,michael@simula.no,ductien.dangnguyen@uib.no,marcus@znipe.se, martin.potthast@uni-leipzig.de,paalh@simula.no

ABSTRACT

This paper describes the approach of the organizers' team for a submission to the GameStory task at MediaEval 2018. Goal of the task is to provide a summary of a match of *Counter Strike: Global Offensive* (CS:GO), a popular e-sports game, that boils down a long game to it's most important events and delivers a story on the progress of the match. Our approach was to provide match statistics and overlay them with events and highlights of the game. We focused on ends of critical rounds, i.e. the rounds where one team took the lead over the other one, and kill streaks, where one player eliminated a substantial number of other players in short time.

1 INTRODUCTION

Broadcasting games over the internet has attracted more and more users over the years [1, 2]. However, beside the technical challenges of low-latency, high quality streaming [4], one also has to deal with the large amount of available data. The GameStory task at Media-Eval 2018 [3] is about summarizing matches or even tournaments in e-sports with particular focus on CS:GO. It is a very new task with a qualitative evaluation, meaning that players and experts take a look at the videos submitted and judge on how well the videos can summarize a given CS:GO match.

Within a CS:GO match multiple influences and events – or the sequence thereof – can decide upon the outcome of a game. First, of course, the skill of the players has a huge impact. Especially visible are those players that take over an offensive role and eliminate several players of the other team in short time. An event like that is called a *kill streak*. Moreover, the decision on how to spend money at the start of a round is critical to the success over multiple rounds.

Our idea was to mainly analyze the development of the game over time and present events in addition to animated game statistics. Focusing on the metadata, we created an animated timeline of the game and used videos from the streams at hand to overlay the events we deemed important.

2 APPROACH

Our approach focused on analyzing and making sense of the metadata, where all events of the game were recorded, including what the players bought, who was killed by whom, when rounds started and ended, and if and when bombs were planted and defused. In a first step, we created an overview on the development of the game following the timeline of the rounds. Figure 1 shows our approach to visualizing the game stats and their development. For

1-0 1-1 2-1 3-1 4-1 5-1 5-2 6-2 FaZe Clan: 0 \$ spent FaZe Clan: 3350 \$ speni FaZe Clan: 14600 \$ spen FaZe Clan: 12400 \$ spen FaZe Clan: 24600 \$ spent Fnatic: 14700 \$ sper Fnatic: 10850 \$ sper Fnatic: 0 \$ spent Fnatic: 5050 \$ spent

Figure 1: Timeline used for visualization with the first 8 rounds. The animation was build using a moving camera of the rounds, each one resembled by one card.

each round, we extracted from the metadata file the current standings, the money spent by each team and eventual kill streaks. For the video, we moved a virtual camera with a resolution of 1920x1080 pixels over the stats, and four of the "stats cards" made up an entire screen. The virtual camera moves with 4 pixels per frames and 30 frames per second (fps), moving one card from one position to the next takes 4 seconds. Each card is visible for 16 seconds, which we considered enough for being able to read the information. For the video, the colors of the stats card have been inverted, as white text on black background seemed to be more pleasant for the viewers who we showed the video to.

For the money spent in each round, we extracted the items bought by the players each round and computed the total amount of money spent per team. For that, we had to create a look-up table (a Python dictionary) based on data from the internet¹, which allowed us to relate the item name to the price, e.g., "ak47":2700, "deagle":300, "flashbang":200, ...

For the kill streaks, we first extracted the kills per round and grouped them by the players. We only considered kill streaks where a single player scored three or more eliminations to be displayed on the statistics in the animated timeline. We further computed the time from the first to the last elimination to be able to find the kill streaks, which happen in short time, for later use in the overlay videos.

With the moving camera animation over the stats cards we then focused on extracting videos from the original streams provided for the GameStory task for overlaying actual game action. The streams have a rather low resolution with 640x380 pixels, but could be used in the left upper and left lower corners of the summary. Based on the kill streak data we extracted videos from the players perspective if the kill streaks were not longer than the number of kills $k \times 6$ in seconds, e.g., 18 seconds for 3 kills, or 24 seconds for 4 kills. The maximum of course is a kill streak of 5, as there are only

Copyright held by the owner/author(s).

MediaEval'18, 29-31 October 2018, Sophia Antipolis, France

¹http://counterstrike.wikia.com/, last visited 2018-10-16

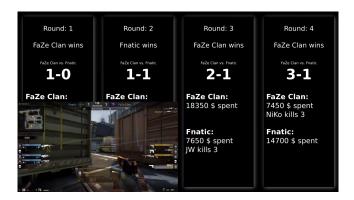


Figure 2: Frame of the final video showing the stats in inverted colors and the overlay of a players view from a kill streak in the left bottom corner.

5 opponents in the game and the players killed do not respawn in the same round. A frame of the final video with the overlay of a kill streak video can be seen in Figure 2.

In addition to the kill streak videos, we extracted the 10 seconds of a round for each round from the commentators view, as well as the map overview focusing on 5 seconds before to 5 seconds after the round end event in the metadata. For the final round, we took out 30 seconds, i.e., round end minus 10 to round end plus 20 seconds.

While up to that point, most of the work done could be done automatically, we then decided to tweak the results with manual input. First of all, we switched from player and team id to the real names of the teams and the players and created the respective dictionaries. We then connected the player names to the streams with a dictionary. With the start times of the matches given for each stream in terms of offset from the beginning, we could related the UTC time-stamps from the metadata file to the respective time point in the stream. However, due to technical constraints, these time points were not matching the actual events too well, so we synchronized them manually at the begin of the first round. The offset for streams from the data given in the metadata ranged from 32 to 45 seconds.

Moreover, we cut the final video manually. The animation was created automatically, but the overlays were done with *OpenShot*, an open source non linear video editor. While the kill streak videos could have been inserted automatically at the beginning of the respective round they took place, the selection of round end videos was up to human decision. We focused on rounds were the tides were turning, i.e., when one team took over the other one, on rounds were teams that spent less money could still score a point, and on the final round.

All kill streaks video sequences were presented in the bottom left corner (see Figure 2), while all beside the last videos concerning the end of game rounds were presented in the top left corner. Only the last video concerning the end of the game was presented in full frame.

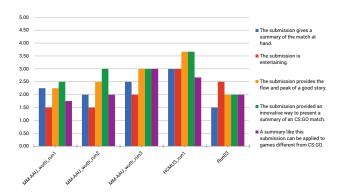


Figure 3: Review scores per run, averaged. 1 is strongly agree, 5 is strongly disagree. Our run is titled *Run03*.

3 EVALUATION

The jury noted that relative to the other submissions our video gave a good summary of the match and presented an innovative way to summarize the match. However, the reviewers noted that the overtime is not explicitly outlined and no in-game videos of that particular period are given, although this is a critical part of the game. The reviewers liked the mix of players' view and commentator's view catching the excitement of the crowd, but all in all, the video was too crowded with the animated stats. The clips seemed somewhat out of place and were not connected – visually or otherwise – to the rounds. Sound only came from the overlay videos, and the periods of silence in between were recognized as missing audio by the reviewers.

4 DISCUSSION & OUTLOOK

The approach we have chosen was mainly based on the metadata, and there only on the economy actions, the round end and the kill streaks. A lot more could have been done including on how the round ended, i.e., by killing the entire enemy team, or by planting or defusing the bomb, or by analyzing the strategy a team applied, i.e. if they saved money by not outfitting their avatars, or if they tried to rush and win the round fast. With extraction of player positions, we could have switched between viewpoints and would have multiple views of the same event.

While we extracted the videos from the map overview and the player position stream, the videos did not make it into the final version. The main problem was the synchronization as there was no solid way to find the right time point in the map stream. A content based synchronization of the videos might have helped with that.

Furthermore, the overlay videos were cut solely based on time stamps. This gave the ill received effect of cut off audio for the final video. In the future, the audio characteristics should influence cutting decisions, i.e., by detecting speech or analyzing the audio envelope to not cut off videos in mid sentence. Moreover, in future work, we aim to base the decision on for which rounds to show the commentator stream at the end on rules in contrast to manual identification.

REFERENCES

- [1] William A Hamilton, Oliver Garretson, and Andruid Kerne. 2014. Streaming on twitch: fostering participatory communities of play within live mixed media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1315–1324.
- [2] Mehdi Kaytoue, Arlei Silva, Loïc Cerf, Wagner Meira Jr, and Chedy Raïssi. 2012. Watch me playing, i am a professional: a first study on video game live streaming. In Proceedings of the 21st International Conference on World Wide Web. ACM, 1181–1188.
- [3] Mathias Lux, Michael Riegler, Duc-Tien Dang-Nguyen, Marcus Larson, Martin Potthast, and Pål Halvorsen. 2018. GameStory Task at MediaEval 2018. In Working Notes Proceedings of the MediaEval 2018 Workshop.
- [4] Karine Pires and Gwendal Simon. 2014. Dash in twitch: Adaptive bitrate streaming in live game streaming platforms. In Proceedings of the 2014 Workshop on Design, Quality and Deployment of Adaptive Video Streaming. ACM, 13–18.