**Computer vision methodology for parsing and processing Valorant match replays**

***Abstract***

We examine the use of computer vision methods to procedurally extract contextual information on player states in real-time from video files or streaming. The nature of such information is dependent on game rules; we combine the collected data with encoded game rules to create metrics which measure player performance based on role.

Depending on the game, we also have access to positional data, allowing for automated tactical analysis and report generation for high-level overviews on teams’ tactical tendencies. We can further extend this quantitative analysis with qualitative analyses of the evolutions of multiplayer games via scheduled, descriptive, game developer update bulletins which detail changes to the game.

Furthermore, we can apply simulation and machine learning methods to this data to practice scenarios for higher preparedness for future matches and make predictions for deeper understanding of future game trends.

The purpose of this application is to reduce the burden of manual opposition analysis for esports teams, provide nuanced metrics and visualizations to understand styles of play and role requirements thoroughly, and make information-driven probabilistic predictions on opposition patterns of play and future game updates. By combining quantitative and qualitative approaches, we can make hypotheses about future game changes and opposition patterns of play via simulation and machine learning methods.

By creating an informational framework for tactical and game-developmental analysis, we seek to provide esports teams with high-quality data and analysis for the purpose of increasing their level of play and being more prepared to face future opponents and adapt to future game development updates.

***Problem***

How do we automate data collection of esports matches in real-time and combine that data with player-base reports written by the developers and simulations modelled by analysts to offer valuable information about opponent playstyles and game developer outlooks to raise esports teams’ level of play and preparedness?

***Solution***

We extract match data from video recordings of games using computer vision for measuring various game-specific measures of performance. We use computer vision and quantitative contextual metrics for automated tactical analysis of matches, computationally recognizing patterns and tendencies of play for granular and high-level reports. We combine this with qualitative analysis of game development updates, professional player input, and overall player-base opinions to make inferences about likely upcoming changes and forecast potential future update trends. We provide an informational framework for simulating and storing match events via the combined quantitative and qualitative analyses, which analysts can use for custom analysis and match preparation via simulation methods and machine learning algorithms. We collect and prepare the collected data from computer vision and simulation methods for input into machine learning algorithms which regress, cluster, classify, and generate valuable information within multiple different contexts and facets of a game. We propose this methodology for offering valuable information about opponent playstyles and game developer outlooks to raise esports teams’ level of play and preparedness.

***Overview***

1. Computer vision
   1. Modern computer vision techniques are more feasible and efficient due to advancements in algorithms and hardware.
   2. Image processing can be used to analyze individual frames of videos to extract pixel information.
   3. Template matching is a method finding a set of matching pixels (the template image) in another image.
      1. By uploading a set of template images (e.g., character images, item images, etc.) it is possible to find these images in video frames and store their locations.
      2. After processing all video frames, the stored locations can be compiled to track the path of the specified object across the screen.
   4. Template matching is used to detect and identify objects (as the specified template). After detecting an object, we can track that same object across the screen using object tracking algorithms.
      1. These methods generally involve using pretrained machine learning models to track an object accurately and consistently across the screen.
      2. The process of training these models on custom objects (e.g., character images, item images, etc.) can be difficult without a large dataset of template images.
   5. Template matching can be used to extract game state information (e.g., health, resource count, etc.).
   6. By combining multiple template matching and object tracking methods, we can extract player state information from the player’s screen. We can store this information in chronological order (a set of player states in order of existence) for all players in a game to provide a comprehensive game state view (including player-independent information like time remaining, objective status, etc.).
2. Contextual metrics
   1. The meaning and perceived value of decisions (which directly lead to actions) in games can vary depending on the game and the particular situation within the game.
   2. The “ideal decision” would be one which incorporates all possible information and acting based on the knowledge of the game state.
   3. In most video games, information is hidden from players by design so that both teams can explore various options and compete.
   4. Compared to traditional games or sports, the speed of decision-making is typically on the millisecond level, so perfectly grasping the constantly evolving game state is near impossible.
   5. Hence, players need to conjecture their opponents’ movements with the information they have and consequently perform actions which they perceive to be the most valuable.
   6. The meaning and value of actions can vary depending on the situation, but generally players decide to make the actions which seem to offer the highest chances of winning (in the short-term and/or long-term).
   7. Thus, game knowledge and experience are required to discern the meaning and values of actions.
   8. Contextual metrics can be measured with the aforementioned computer vision methods
      1. These are designed based on the game and player role, for a complete understanding of why the metric matters in a particular game for a particular role.
      2. These metrics incorporate the player states and the comprehensive game state to verify integrity of measurement and estimate actions’ values.
      3. An example of such a metric would be the value of decoy movement.
         1. If player(s) make actions in a particular area, opponents must spend their awareness to react to that play, creating weaknesses in other areas that can be exploited.
         2. By tracking and storing all the player positions and other game information, we can measure the value of such decoy actions by the eventual outcome.
         3. Doing this at scale allows for aggregation and statistical modelling to better understand the distribution and mechanics of certain types of actions depending on the game situation.
3. Automated tactical analysis (quantitative)
   1. When preparing for matches and tournaments, coaches and analysts must watch many relevant opposition matches to understand their playstyle and behaviors.
      1. Across many games, they aggregate observations to grasp general opponent player tendencies given contextual situations (e.g., map, phase of match, position, enemy resources available, etc.).
      2. Doing this manually is time-consuming and prone to risk of human error and bias.
         1. For smaller teams with one or few coaches and/or analysts, the amount of video to parse through is overwhelming.
         2. Humans can also be biased by personal preferences and past experiences.
         3. This can potentially reduce the quality of analyses and consequently diminish the team’s performance.
   2. Patterns of opposition play which cannot be seen with the human eye and mind can be analyzed with an algorithm which automatically collects and labels data using the aforementioned computer vision methods and contextual metrics.
   3. This can be done for all player states in chronological order, and in games that provide “minimaps” (a small heads-up display showing the player’s and teammates’ positions) it can also include position as an attribute of the player state (*Figure 1, Figure 2*).
   4. The data can be stored in a custom internal model which can then be programmatically converted into various human-readable formats (e.g., txt, csv, pdf) (*Figure 3, Figure 4*).
   5. Depending on the customer requirements, analytical reports can be produced to lessen the burden of analysis on the esports team.
   6. By offering high-level overviews and thorough game analysis (created with a mix of experienced game analysts and automated algorithms), the customer receives pertinent and valuable information on their own and opposition playstyles without the effort of manual analysis or data interpretation.
4. Game developmental analysis (qualitative)
   1. All esports are online multiplayer games in which teams of one or more players compete against each other. Games evolve over time as the developers iterate and improve their games.
      1. Changes can be made for balancing purposes to make games fairer and ensure that no single role or item or side has a strictly dominant advantage which reduces competition.
      2. Changes can be made to change the concepts and rules of a game to match the developer’s ideal vision of the game and its evolution.
      3. Changes can be made to improve the performance of the game (as an application).
      4. Changes can be made in response to the opinions of the professional esports player community and/or the casual player-base for players’ quality of life.
   2. By cataloging the development updates of a game (described in developer patch notes) from the inception of the game, we can create a timeline of game changes to view chronological progression.
   3. Just as art and sports are analyzed within the context of the time and state of culture, the evolution of a game can be analyzed by experienced analysts to make informed probabilistic predictions (a range of potential future trends ranked from most to least likely to be enacted) about the future of a game’s development.
   4. By understanding the ebbs and flows of the updates and combining that knowledge with a strong understanding of both professional player and overall player-base opinion on various game matters (collected via personal interviews, social media surveys, etc.), experienced game analysts can make granular predictions about upcoming changes and broad predictions about long-term progression.
5. Simulation & machine learning for predictive analytics
   1. With the informational framework described thus far, analysts can simulate a variety of specific and broad match events to test tactics and visualize the potential outcomes.
      1. The sensitivity of individual and team setups can be measured by varying the simulation parameters and conditions (e.g. map, phase of game, position, enemy resources available, etc.).
      2. Over many simulations informed by past match data and aforementioned analytical methods, analysts can estimate the conditional probabilities of certain events occurring at certain positions and/or certain times, given sample data.
      3. Esports team coaches and analysts can apply tactical periodization methods in training and practice matches which simulate many probable and some improbable in-match situations in order of appearance/occurrence in official matches (Bordonau & Villanueva).
   2. Matches and simulations can be stored in a machine-readable format (e.g. dataframe, JSON, csv, etc.) which analysts can use as input for machine learning algorithms.
      1. Analysts can apply regression methods on quantitative metrics to predict performance categorized by various attributes (e.g. map, phase of game, position, enemy resources available, etc.).
      2. Analysts can apply regression methods on quantitative metrics to predict performance over time across multiple matches (e.g. a league season or tournament).
      3. Analysts can apply clustering and semantic similarity methods to query databases of past matches and simulations for similar events and sequences of events.
      4. Analysts can apply generative methods on sequences of events to model new potential sequences based on past matches and simulations (DeepMind). This approach can be augmented by “semantic style transfer” methods which can simulate sequences of events according to an attitude or strategic approach (e.g. highly aggressive, slightly passive, patient, late rush, etc.). These styles can be learned by training models on a large amount of data that is determined by human analysts to fall within certain categories (i.e. analyst bias strongly influences training of such models).
      5. Analysts can apply classification methods on developer patch notes to assess the general approach of the development team for a particular update. Because much less data will be available for such analysis, machine learning methods like one-shot learning can be applied to predict the likelihood of subsequent effected updates (e.g. game health update, map update, rule update, etc.) based on the current and previous updates.
   3. By repeating many simulations many times, teams can increase their preparedness for matches. By creating simulations for training, analysts are simultaneously creating data for machine learning algorithms that can output metrics, insights, or sequences of events for further analysis.

***Conclusion***

We seek to automate data collection of esports matches and combine that data with player-base reports written by developers and simulations created by analysts. We use a variety of methods for accurately collecting, preparing, analyzing, and reporting data and insights. Thus, we can regress, cluster, classify, and generate valuable information within multiple different contexts and facets of a game using the processed data. By creating an informational framework for tactical and game-developmental analysis, we seek to provide esports teams with high-quality data and analysis for the purpose of increasing their level of play and being more prepared to face future opponents and adapt to future game development updates.

The esports industry generated about $800 million in the year 2022 from sponsorships, advertising, and media rights (Gough). The online nature of multiplayer games naturally lends itself to modern social media outreach, appealing predominantly to the demographic of younger males who grew up and live in internet culture. Because of the internet popularity of esports among young people, the sponsorship and advertisement placements boast major companies (e.g. Amazon, Honda, Red Bull, etc.) actively competing for visibility in esports events and online livestreams. The majority of this revenue is generated in Asia and North America.

The most popular sport in the world, football, had its most expensive clubs generate about $ 8 billion in revenue overall in 2021 (*Deloitte Football Money League 2022*). These same top clubs reached a peak total generated revenue of $ 9 billion in 2019, displaying the financial growth opportunities of a widely beloved activity that can be viewed globally.

The esports industry is not appealing to new viewers because of the multitude of video games, all with different rules and styles and visuals. The lack of understandability and consistency makes it more inaccessible than traditional sports despite similar strength of sponsors and advertisement presences. Through our informational framework, we wish to increase global awareness of esports with brief and easy-to-understand articles, reports, and visualizations.

Just as sports like baseball and football gained popularity in conjunction with the growth of their respective data industries, we hope to do something similar with esports. By offering our data-driven insights, our goal is increasing the level of play and preparedness for teams. We plan this to be a starting point for outreach to fans and brands, using feedback from teams to refine and rework our products and reports, so that we can make esports more interesting, understandable, and enjoyable for everyone.

We have discussed in detail the benefits, but the primary costs of our informational framework are the costs of time, money, and labor to hire coaches and analysts. To develop a successful data analytics system for an esports team, the team philosophy and owner vision need to align, requiring solid and consistent short- and long-term objectives for data analytics initiatives which will help the team improve their performance. The other potential cost is privacy, as we will need access to teams’ data with their consent to provide custom metrics, simulation methods, and machine learning algorithms for their respective initiatives. This is an optional cost, as we can offer plans purely for data collection, or purely for reports and visualizations, or something of that nature. Beyond these 2 costs, the effort required on part of the esports team is almost nonexistent (besides application of the data-driven insights in training and competition).

Ultimately, more granular and specific metrics combined with suitable communication and visualization produce more entertaining broadcasts for expert and casual viewers of esports. Furthermore, the level of play can be raised through more informative insights and increased creative freedom for coaching staff. Our product aims to achieve these goals through an informational framework which parses frames of broadcast video, collects and analyzes spatiotemporal positions and statuses, and delivers comprehensive analytics via tabular metrics and visualizations over time and space.

***References***

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* ***Figure 1***

A screenshot of a computer

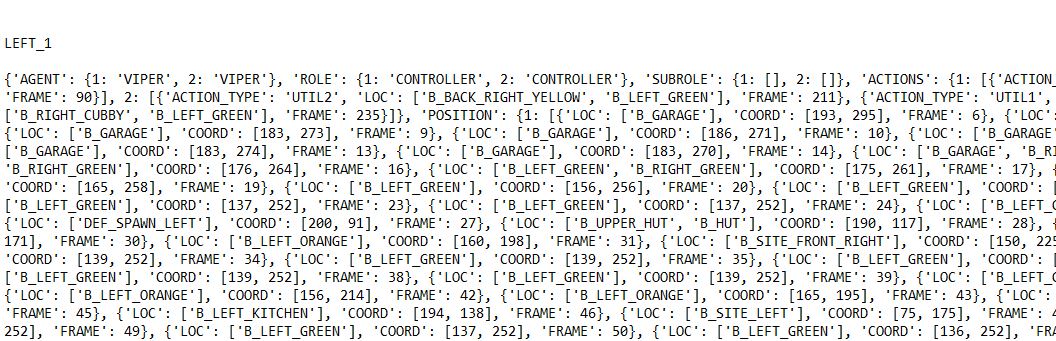
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* ***Figure 2***

***Diagram

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* ***Figure 3***

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* ***Figure 4***

A screenshot of a computer

Description automatically generated with medium confidence