Masters of Control: Behavioral Patterns of Simultaneous Unit Group manipulation in StarCraft2

Authors : Eddie Q. Yan, Jeff Huang, Gifford K. Cheung

Published in CHI '15 Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems

AEIS Lab
Ajou Embedded Intelligent Systems Laboratory

Sep. 27^{th} 2016
Seungmin Kim

Contents

- Background
- About this paper

Background

- Purpose of presentation this paper
- What is HCI?
- About my project

Purpose of presentation this paper

- Ongoing Project
  - Emotion gaming project
- Introduction of HCI domain
  - Human-Computer Interaction(HCI)
- How the authors describe a paper in HCI domain

What is Human-Computer Interaction(HCI)?

- HCI is the study of interaction between users and computers
  - Computer science & AI
  - Cognitive science
  - Sociology
  - Psychology
  - Design
- In HCI domain, people are interested in
  - User experiences
  - Designing user interfaces
  - How human action is structured
  - Human-information processing

Emotion gaming project - ongoing

- The Contribution defined as
  ① Using both physiological sensor and mobile phone, we could analyze player's emotional status.
  ② Is going to be the number of emotions that we could analyze, and the accuracy will be added.
  ③ The interaction of multiple players' emotions is applied to mobile application.
- Ideas for application
  ① Difficulty adjustment
    - Modify game's difficulty using analyzed player's emotions.

  ② Advertisement optimization
    - Showing ads. decided by player's emotions in the proper way.

  ③ Affective game control
    - By analyzing emotions, the application gives a advantage to player.

General experiment scenario

- The whole session is less than 5 mins
  1. Every 10-second-small segment, we are going to analyze emotions.
  2. Pick **few important events** during the whole session
  3. Use video, sensors to capture ground truth
     1) Kinect plus computer vision approach
        - **Facial expression**
     2) PPG, GSR, accelerometer, touchscreen, microphone
        - E4-wristband
        - Mobile phone’s sensors

PPG

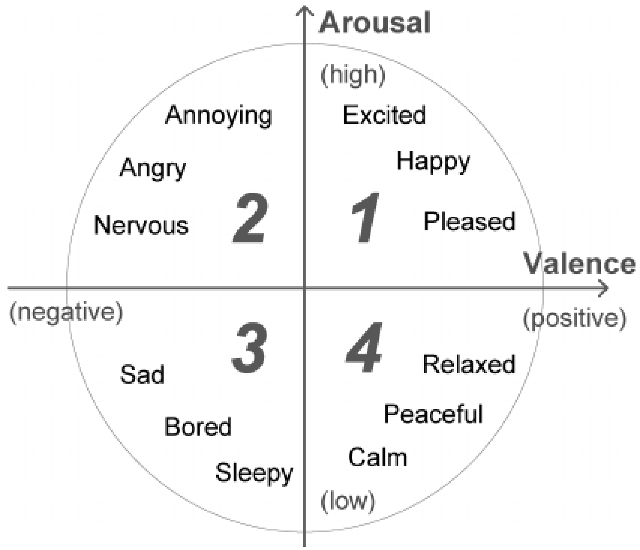
GSR

What we get from experiments(1)

I. Emotions
   - Calm(Valence) versus Arousal
     A. Russel affective model

II. Play style
   - Aggressiveness
     A. The taylor competitive reaction time test(TCRTT)
     B. Hot sauce paradigm
     C. General aggression model(GAM)
     D. Aggression Questionnaire
   - Competency
     ✓ Finding a way to assess it.

III. Eagerness
   - How much the player focused in game
     I. Record the whole session
     II. Via survey, eagerness will be treated as data



Russel affective model

What we get from experiments(2)

I. Self-assessment gamer's competency
   - Via survey, player judges his/her gaming performance themselves.

II. General gaming experience
   - Via survey, we use it for finding a way to apply it.

About this paper

- Keywords
- Summary
- Contributions
- Analysis metric & results
- Pros & Cons
- Conclusion

Keywords(1)

- Control group
  - Optional mechanism that allows players to control multiple units
    - Game interface
- Keystroke-level modeling(KLM)
  - Distinguish each key press is meaningful or not.
- Actions per minute(APM)
  - One of the features that identify skilled players
- Support vector machine(SVM)
  - Machine learning technique
- Leave-one-out cross validation(LOOCV)
  - Validation technique

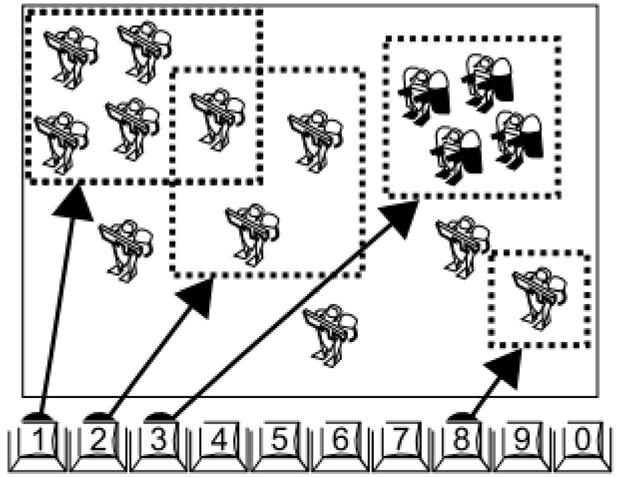


Figure 1: Control groups are bound to keyboard keys 0–9 and represent groups of units. Different groups can include the same units, or no units at all.

Keywords(2)

- Macro
  - Actions maintain the player's economy to keep income and production optimal
    - Built new buildings, training new workers
- Micro
  - Actions optimize the effectiveness of individual units
    - Scout, fight

Paper summary

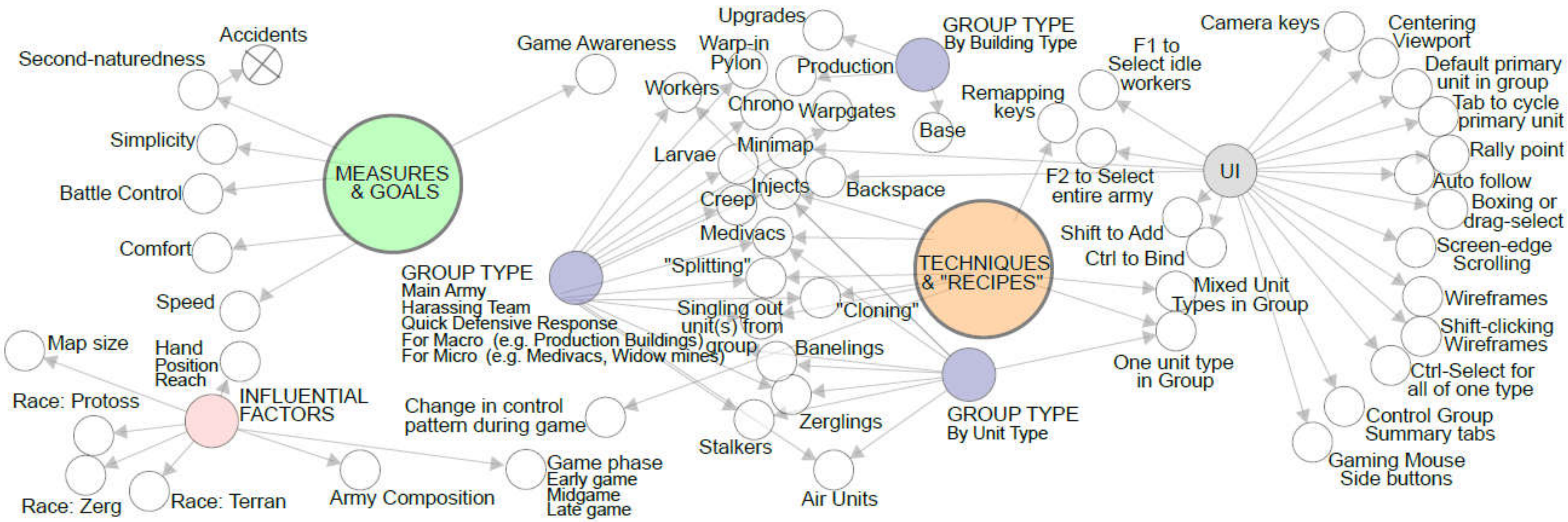
- Analysis of Starcraft 2 “replay” files
  - To understand the characteristics of “control group”
  - To analyze players’ behavioral patterns
    - Warmup, Group control usage, macro selection, rebinding group control
  - In total, 3316 replays were analyzed
    - Representing 2540 players
- Classify skill levels of players using machine learning technique
  - SVM
  - Leave-one-out cross validation(LOOCV)
  - Classify into three classes
    - Novice for bronze, silver league
    - Proficient for platinum, master league
    - Expert for grandmaster league

Contributions

- Analysis of a variety of player control group behaviors
  - Quantitative
  - Qualitative
    - Collected and analyzed by forum's and social website's post and comments
- Investigate control group habits among players
- Discuss the characteristic of control groups

Analysis metric

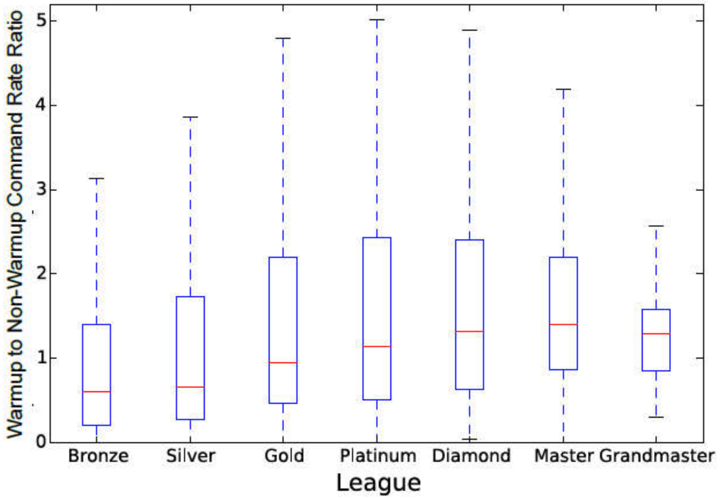
- KLM-based analysis of starcraft2 interface
- Actions per minute
  - Convert it to commands/second



< Figure 2: Diagram of themes and selected sub-categories from our qualitative analysis >

Analysis Results(1)

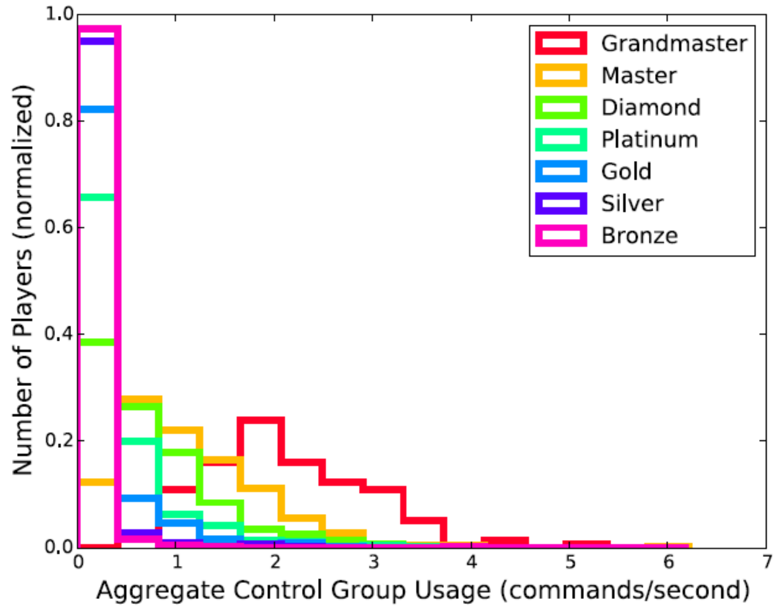
- Differences between skill levels
  - Warmup



< Figure 3: Warmup to non-warmup control group usage ratio >

League	Median Warmup Command Rate	Median Non-Warmup Command Rate
Bronze	0.012	0.020
Silver	0.023	0.052
Gold	0.125	0.143
Platinum	0.307	0.229
Diamond	0.782	0.482
Master	1.377	0.901
Grandmaster	$\boxed{2.360}$	$\boxed{1.907}$

< Table 2: Median warmup and non-warmup command rates >

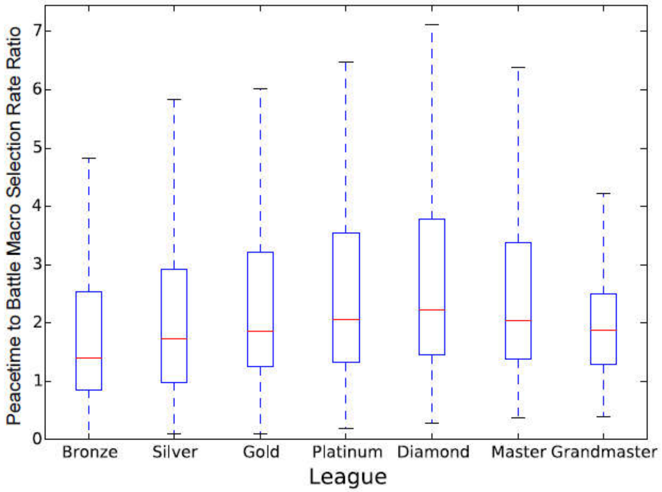


< Figure 4: Distribution of control group usage among the leagues >

- everyone in grandmaster league uses control groups to some extent, with the majority executing around two control group commands per second

Analysis Results(2)

- Differences between skill levels
  - Macro selection



< Figure 5: Ratios of macro selection rates via control groups during peacetime vs battle >

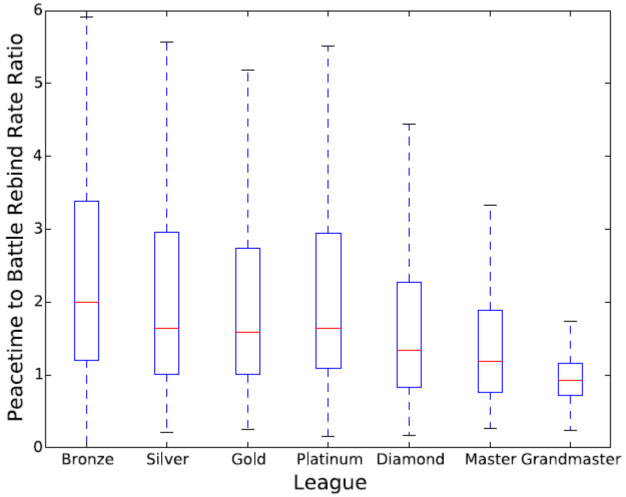
League	Median Peace Selection Rate	Median Battle Selection Rate
Bronze	0.011	0.002
Silver	0.036	0.020
Gold	0.114	0.058
Platinum	0.216	0.098
Diamond	0.422	0.161
Master	0.752	0.317
Grandmaster	**1.332**	**0.712**

< Table 2 : Median macro selection rates during peace-time vs battle >

- Expert users' macro selection rate in battle quite close to master league player's rate in peacetime

Analysis Results(3)

- Differences between skill levels
  - Rebinding Control groups in battle



< Figure 6: Ratios of control group rebind rates during peacetime vs battle >

League	Median Peace Rebind Rate	Median Battle Rebind Rate
Bronze	0.006	0.000
Silver	0.010	0.000
Gold	0.019	0.004
Platinum	0.027	0.009
Diamond	0.037	0.022
Master	0.054	0.047
Grandmaster	**0.088**	**0.097**

< Table 3 : Median control group rebind rates during peace-time vs battle >

- High-skilled player are more vigilant about managing newly produced units

Analysis Results(4)

- Skill classification
  - Classifying skill from control group usage

League	Mean	Median	SD	Min	Max
Bronze	0.076	0.036	0.188	0.000	2.317
Silver	0.118	0.057	0.204	0.000	1.710
Gold	0.261	0.139	0.283	0.000	1.818
Platinum	0.396	0.254	0.379	0.002	2.853
Diamond	0.581	0.500	0.390	0.006	2.861
Master	0.754	0.676	**0.430**	0.039	**3.801**
Grandmaster	**0.955**	**0.914**	0.378	**0.096**	2.452

Table 4: Player to player distance statistics at different skill levels (in units of commands/second)

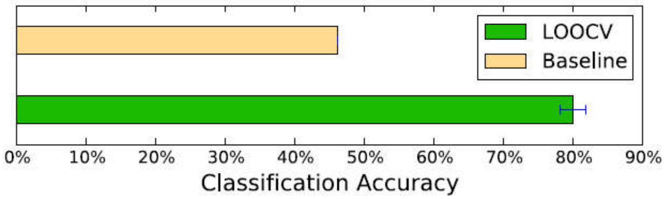


Figure 7: Skill level classification performance of {novice, proficient, expert} players estimated via LOOCV compared to baseline classification performance from choosing the most frequent class. Here, the error bar represents the 95% confidence interval for LOOCV accuracy.

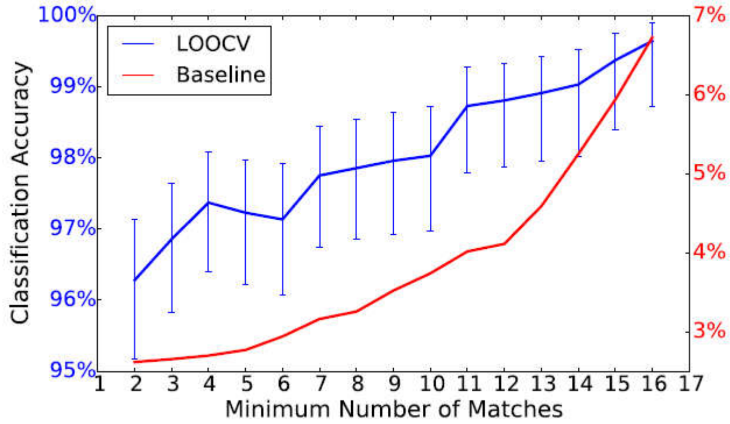


Figure 8: Classification performance of identifying expert players from control group features estimated via LOOCV compared to baseline classification performance.

- Using LOOCV, classification accuracy is much more better than just selecting most frequent class(for cross-validation).

Pros & Cons

- Pros
  - Used lots of data to analyze
    - Quantitative
  - Used various proper metrics to analyze data
    - Qualitative
  - Analysis of data in various perspective

- Cons
  - With lots of data analyzed, authors could research about the interfaces of computer games
  - Some graphs doesn’t seem to be needed because its ambiguous

Conclusion

- This paper analyzed in-game-play data to get behavioral patterns of players, especially expert gamers
- The authors mentioned about future work, but it is only about finding a value from meaningless warmup.
- Learned from this paper
  1. A way to describe paper in HCI domain
  2. Various way to analyze data and human actions