Towards a Better Understanding of Chess Players' Personalities: A Study Using Virtual Chess Players

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Towards a Better Understanding of Chess Players' Personalities: A Study Using Virtual Chess Players

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Abstract. Virtual humans emerged as a topic of research in HCI and they have been used for various purposes. This paper explores the behavior of chess players in a virtual chess environment to gain more understanding about chess personalities. In particular, the focus of this research is investigating attack and defense strategies used by virtual chess grandmasters against different virtual class-B personalities who vary in their strength in the different stages of a game. These attack and defense strategies have attracted much attention in the chess community and are considered among the main aspects to chess players. They occur in different phases of the game: opening, middle game and endgame. The researcher examines virtual chess players to understand the psychology of competition between two grandmasters (attacker, defender) and three class-B chess players with different personalities: (a) strong at openings; (b) weak at openings, but strong at endgames and (c) balanced player. The virtual humans in this research represent personalities of real players. The empirical players' results showed that the personalities could influence the error and the number of moves of the game for both grandmasters and class-B players. Such findings can be used in designing virtual chess players.

Keywords: virtual humans, chess, attack, defense, personality

1 Introduction

Computer chess has grown very rapidly in the last 30 years. This was the result of many achievements which demonstrated how computers could change the game of chess including a computer being able to defeat the world champion, Gary Kasparov [21]. One of the most significant achievements in the AI chess is the development of virtual chess players. These are imaginary players with various personalities associated with chess (i.e. attacker and defender). They are introduced by companies such as Titus and Ubisoft [4, 30]. Such virtual humans represent real chess players such as Kasparov and Anand and play at almost the same level of strength.

In this research study, chess personality is defined as the attitude of the virtual chess player during the chess game such as attack or defense. This can reflect the player's strength and weakness during certain phases of the game (i.e.

opening, middle and endgame). Different chess players have different attitudes towards the opponent which shape their personalities during the game.

Exploring chess personalities is important for many reasons. First, it can help chess developers design chess programs which simulate humans. Second, it can help in understanding the behavior of human players by identifying the reasons on why players lose games which can be a challenging task [29]. Interestingly, understanding chess personalities can pave the way for a new direction of research in the medical field. Research shows that the Chessmaster software improved surgical training undertaken in a virtual environment [26].

Each virtual player has a rating, which is a number that measures the relative skill of the player in his games against other players in the chess community [11]; the higher the rating, the stronger the chess player. Organizations such as United States Chess Federation (USCF) and the World Chess Federation provide these ratings to chess players. Players can be distributed into different classes based on their rating. For example, in the USCF System, a senior master has a rating of 2400 and above; a master's rating ranges from 2200 to 2399; expert from 2000 to 2199; class A from 1800 to 1999; class B from 1600 to 1799 and class C from 1400 to 1599 [12].

In this paper, five Ubisoft virtual humans are examined: two grandmasters and three class-B players [30]. These players vary in their personalities. Two chess grandmaster personalities were selected: Supreme Defender and and Early Attacker against three class-B player personalities: A personality that is strong at the endgame, but plays weak openings; A personality with strong openings; and a balanced player. This research explores the following questions:

- How do virtual grandmasters with identical ratings and different personalities (attacking and defensive) perform while playing against various chess-B players with different strengths at each phase of the game?
- How do virtual class-B chess players of different personalities reflected in different phases throughout the game, behave whilst playing against virtual grandmasters with different personalities (i.e. attacker and defender)?
- Do virtual grandmasters make more errors when they play against a virtual class-B player who is strong at the opening as opposed to a class-B player who is strong at the endgame and plays vulnerable openings?

2 Related work

Chess has been an attractive domain for researchers of different fields. An early work aiming to understand the psychology of chess players was done by de Groot, a psychologist who studied chess players of various skills [9]. de Groot constructed meaningful chess patterns and then asked chess players of various skills to reconstruct them from memory. He found that chess masters outperformed novice players. A follow up was done by Chase and Simon [6] who studied chess players of different strengths and found that masters learn more than novice players. The two studies show that chess masters are able to detect patterns of pieces over the chess board, which allows them to play a stronger game using memorized moves in a short amount of time as opposed to novice players. These classical studies were subjected to further research and development in many perspectives. Powell et al. [22] utilized fMRI in male beginner chess players to locate the cortical parts in the brain related to chess. Similarly, Burgoyne et al. [3] investigated the connection between chess and cognitive skills. Their findings revealed a positive correlation between chess and fluid reasoning, comprehension-knowledge, short-term memory and processing speed.

Chess rating is used as a metric to measure the strength of each player against others in the community. Players can be classified into different categories (i.e. grandmasters, class-A players) according to their rating. A considerable amount of classical literature has been published on chess ratings and class-B players. For example, Calderwood et al. [5] investigated the influence of time pressure on class-B players and grandmasters. Their research supports the classical findings that players with high rating depend on pattern recognition more than less skilled players. Similarly, Goldin [15] investigated chess players of various classes and their findings were consistent with those of Calderwood et al. [5]. Likewise, Sheridan and Reingold [27] investigated eye movements of chess players that vary in their skill and found that reaction times were faster for experts than less skilled players. In a different vein, Lane and Chang [18] conducted tests involving chess positions and their findings support the evidence of the significance of pattern recognition in making strong moves among skilled chess players.

Chess players of various levels (i.e. grandmasters and class-B players) vary in their personalities. For example, some players might have an attacking attitude, while others might be more defensive and some could be a mixture of both. These attitudes can be clearly seen in different phases of the game. Various studies in the literature of artificial intelligence and cognitive psychology investigated these attitudes. For example, Botvinnik [2] explored attack and defense in solving chess tasks and calculated a function for an attack path. Attack and defense are also among the most important characteristics of chess personalities. These personalities have not only attracted the attention of researchers from the AI domain, but they are also of great interest to cognitive psychologists. An example is the study by Saariluoma [25] who asked players to detect quickly whether the king was attacked or not. He found that skilled players were faster than others who were less skilled in completing the task. Chess pieces are essential pieces of attack and defense in chess and have also been explored in the literature by Rasskin-Gutman [23].

Virtual chess players have been examined in research through different perspectives. Kovács et al [17] developed a virtual chess player which applies different styles in communication such as perceiving the emotions and talking with the opponent. While developing a virtual human is a commendable work, their study did not provide any quantitative analysis of its performance. Along with virtual chess players, the extensive research revealed existing literature in the area of virtual humans and their applications in different fields. One example is SimSensei Kiosk, which acts like a human nurse and communicates with patients [10].

Similarly, Kenny et al. [16] applied virtual humans in diagnosis and training. These virtual humans used in the medical field can have many advantages. For instance, a person can disclose more information to an agent than what they provide to a human [20, 24, 28]. Virtual humans behave to a significant extent like real human beings [28].

Although there has been existing research on virtual humans in chess and other domains, the extensive literature review did not reveal any study that involved analyzing the personalities of virtual chess players and the differences between them when they play against each other. In other words, all the previous studies did not explore the error rates of different chess personalities and how they perform while playing against other chess personalities. The extensive literature review revealed that this is the first HCI study that analyzes chess personalities of virtual chess players. Chess players' personalities may have an impact on the chess game, thus they need to be explored further. In addition, they might help researchers further understand the behavior of people in real life settings.

3 Experiment

The focus of this experiment is to understand the relationship between errors, number of moves and personalities of different virtual humans. The goals of this experiment are:

- Explore the errors made by virtual grandmasters (attacking, defensive) while playing against virtual class-B players with various strengths at different phases of the game.
- Examine the errors made by virtual class-B players with different strengths in the game phases while playing against virtual grandmasters of different personalities.
- Investigate the relationship between the numbers of moves in a game and the two virtual chess personalities which compete against each other

3.1 Participants

For this experiment, five virtual chess players offered by Ubisoft [30] were selected. These players come with different personalities. In this study, there are two grandmaster personalities: Anderssen (Early Attacker) and Leko (Supreme Defense). The three class-B player personalities the researcher picked are: Josh (vulnerable openings, but strong endgame), John (strong openings), and Kanna (Balanced player).

3.2 Materials

The design involves the manipulation of two independent variables as follows:

- The personality of the grandmasters was manipulated. Half of the games in this experiment were played by a grandmaster with an early attacking personality (Anderssen) and the other half were played by a grandmaster with a supreme defensive personality (Leko). The two virtual grandmasters have the same USCF rating of 2971.
- The class-B player personality was manipulated according to the strength he demonstrated in different game phases. Three virtual personalities were selected: Waitzkin who is strong in endgame but weak at openings, John who plays strong openings, and Kanna who is a balanced player. The USCF ratings of the three players are almost identical: Josh's USCF rating is 1600, John's rating is 1631, and Kanna's rating is 1623.

The color of the grandmaster was used as between-subjects factor. In this experiment, there are five dependent variables measured by the Chessmaster [30]:

- The total error of the virtual grandmaster
- The total error of the virtual class-B player
- The relevant error of the virtual grandmaster
- The relevant error of the virtual class-B player
- The number of moves in the game

In this research, the move is defined as the white player's move followed by the black player's move. The metrics total and relevant errors [7] are calculated by the Chessmaster offered by Ubisoft [30]. The total error is defined as the difference between the moves players choose and the optimal ones they could make. The relevant error is defined in the same way, but it focuses on the moves where the outcome of the game is still not clear yet. The Chessmaster did not provide any details on how the total and relevant errors are calculated and the two definitions were obtained from [7].

The criteria for choosing the virtual chess players in this research are the following:

- All virtual grandmasters have the same rating. They only differ in personalities.
- The virtual class-B players have almost an identical rating. However, they vary in their strength in different game phases.

3.3 Procedure

Each grandmaster played 102 games against each class-B player. In order to reduce the chance that a player's color influences the design, each player plays half of the games in the experiment with white color and the other half with black.

4 Results

The dependent variables were recorded for each game in the experiment. Each dependent variable was submitted to two grandmaster personality styles (Leko and Anderssen) by 3 class-B player personality styles (Josh, John and Kanna) repeated measures ANOVA. The color of the grandmaster was used as between-subjects factor. All effects were reported as significant at $p < 0.05$. Mauchly's test was used for sphericity testing and Greenhouse-Geisser correction was applied if the assumption of sphericity was violated.

4.1 The total error of the virtual grandmaster

The main effect of the grandmaster's personality is significant, $F(1, 100) = 13.975$, $p < 0.001$, indicating that the total errors of Leko ($M = 1.874, SD = 0.119$) are larger than the total errors of Anderssen ($M = 0.954, SD = 0.119$). Moreover, there is a significant main effect of the class-B player's personality, $F(1.809, 180.910) = 5.338$, $p = 0.007$. Contrasts reveal that the total errors of grandmasters when playing against John ($M = 2.010, SD = 0.289$) are larger than the total errors of grandmasters when playing against Josh ($M = 1.102, SD = 0.170$), $F(1, 100) = 7.826$, $p = 0.006$ and when playing against Kanna ($M = 1.117, SD = 0.187$), $F(1, 100) = 6.251$, $p = 0.014$.

4.2 The total error of the virtual class-B player

The main effect of the grandmaster's personality is significant, $F(1, 100) = 74.734$, $p < 0.001$. This indicates that the total errors of the three class-B players against a grandmaster with a defensive style ($M = 11.885$) are larger than the total errors of the class-B players against a grandmaster with an attacking style ($M = 8.534$). In addition, the main effect of the class-B player's personality is significant, $F(1.873, 187.281) = 12.356$, $p < 0.001$. Contrasts reveal that the total errors of Kanna ($M = 11.738, SD = 0.384$) are larger that the total errors of Josh ($M = 9.189, SD = 0.303$), $F(1, 100) = 26.911, p < 0.001$ and the total errors of John ($M = 9.701, SD = 0.434$), $F(1, 100) = 11.248$, $p = 0.001$.

Figure 1 shows the mean total error of grandmasters and class-B players while playing against each other. A defensive grandmaster makes more mistakes than an attacking grandmaster. Furthermore, a balanced player makes more mistakes than the two players who are strong in opening and endgame.

4.3 The relevant error of the virtual grandmaster

The main effect of the grandmaster's personality on the relevant error of grandmasters is significant, $F(1, 100) = 13.958$, $p < 0.001$. This indicates that the relevant errors of Leko ($M = 0.316$, $SD = 0.059$) are larger than the relevant errors of Anderssen ($M = 0.069$, $SD = 0.028$).

4.4 The relevant error of the class-B player

The main effect of the grandmaster's personality is significant, $F(1, 100) = 30.177$, $p < 0.001$. This indicates that the relevant errors of class-B players

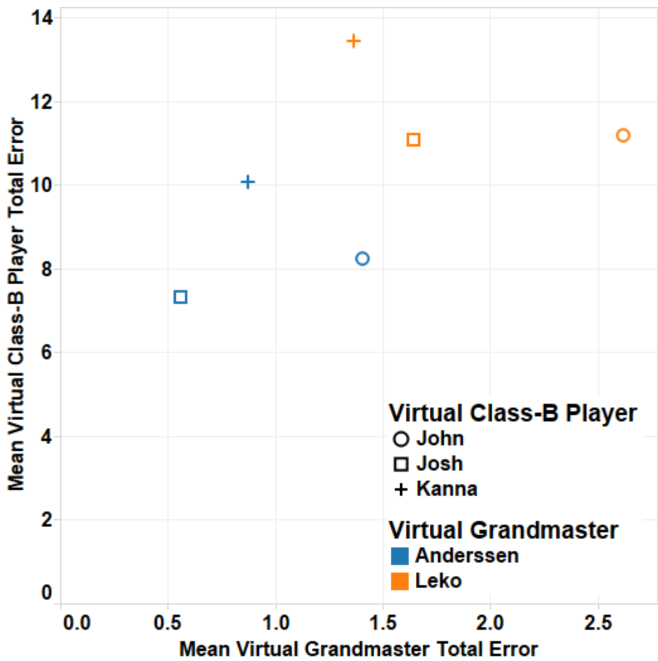

Fig. 1. Mean total error of virtual class-B players and grandmasters

playing against Leko ($M = 3.390$, $SD = 0.115$) are larger than the relevant errors of class-B players playing against Anderssen ($M = 2.543$, $SD = 0.096$). Furthermore, the main effect of the class-B player's personality is significant, $F(2, 200) = 16.104$, $p < 0.001$. Contrasts revealed that the relevant errors made by Kanna ($M = 3.581$, $SD = 0.110$) are larger than the relevant errors made by Josh ($M = 2.6$, $SD = 0.13$), $F(1, 100) = 31.166$, $p < 0.001$ and John ($M = 2.717$, $SD = 0.15$), $F(1, 100) = 19.862$, $p < 0.001$. Figure 2 shows the mean relevant error of virtual class-B players and grandmasters in this experiment.

4.5 The number of moves in the game

The main effect of the grandmaster's personality is significant, $F(1, 100) = 12.740$, $p = 0.001$. This indicates that the number of moves played by a grandmaster with an attacking style ($M = 45.516, SD = 0.601$) is higher than the number of moves played by a grandmaster with a defensive style ($M = 42.729, SD = 0.0.538$). The main effect of the class-B player's personality is also significant, $F(1.676, 167.627) = 30.361$, $p < 0.001$. Contrasts reveal that the number of moves in games played by grandmasters against Josh ($M = 46.368, SD = 0.639$) or John ($M = 46.093, SD = 0.882$) is larger than the number of moves in games played by grandmasters against Kanna ($M = 39.907, SD =$

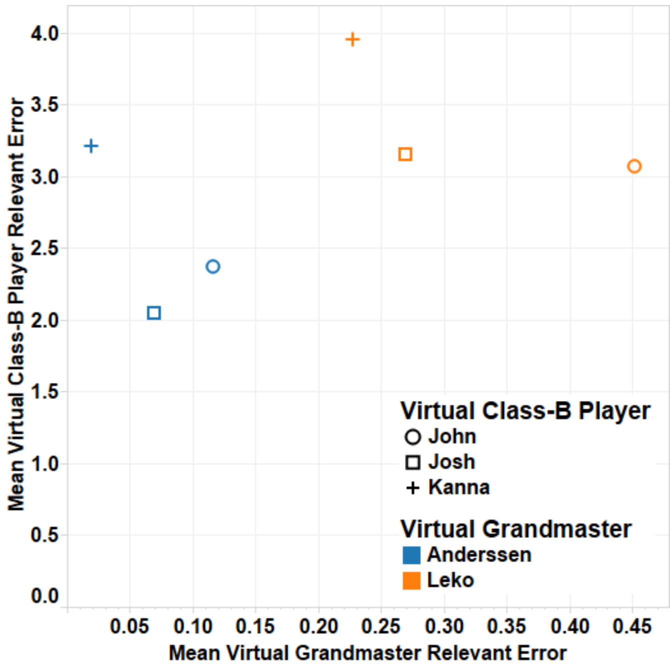

Fig. 2. Mean relevant error of virtual class-B players and grandmasters

0.459). Figure 3 shows the mean number of moves in games between virtual grandmasters and class-B players where more moves are associated with an attacking grandmaster. Additionally, games against Kanna have the least number of moves.

5 Discussion

The empirical results showed that a grandmaster with a defensive style tends to have a higher error than a grandmaster with an attacking style when playing against players with different strengths in the various game stages (Figures 1 and 2). This is probably because an attacker grandmaster has built-in attacking traps and can take control of the game, which makes him less subject to errors than a grandmaster who plays defensively and must respond to the attacks from an opponent.

In addition, this study explores the performance of three class-B players who differ in their strength during the different game phases (i.e. player who plays strong endgames and weak openings as opposed to a player who plays strong openings and weak endgames). The findings revealed that the players' strength in different phases influenced the total and relevant errors of class-B chess players during their games against attacking and defensive grandmasters.

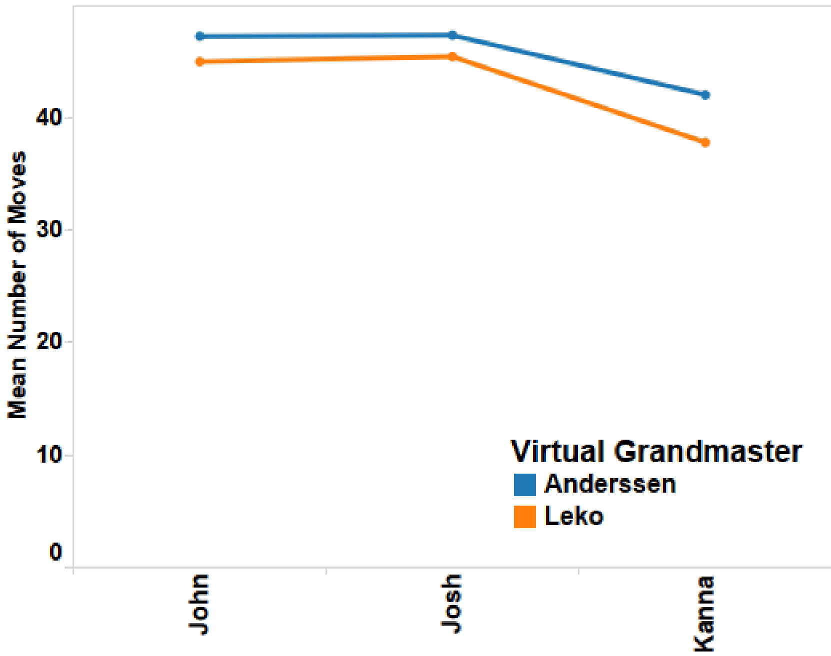

Fig. 3. Mean number of moves

The results showed that a class-B chess player who is strong at either the opening or endgame performs better than a player who is balanced when playing against a grandmaster with attacking or defensive style. For example, Josh who is very sharp at the endgame and John who had strong openings performed better than Kanna despite that the three players have almost the same rating. These findings show the importance of studying chess openings and endgames.

The grandmaster personality had an effect on the class-B players at different stages of the game: The errors of the class-B players were always higher when they played against a grandmaster with a defensive style. A plausible psychological explanation is that people naturally try to understand the cause of difficult events and how they can affect their lives when they encounter them [31, p. 285]. Thus, an initial attack during the game probably makes class-B players try to understand the scenarios deeper at an early stage than when they are playing against a defensive grandmaster who does not initiate an attack.

As for class-B players, the player who was balanced during all stages of the game had a higher error than a chess player who was sharp at either the opening or the endgame stage. On average, grandmasters could beat a class-B player with a balanced style with less number of moves as compared to a player who is strong at either opening or endgame. This shows the importance of the opening training in the game, which is also supported by other researchers in the chess literature

[13, 19]. Similarly, the results indicate that the endgame is as important as the opening phase to the game's outcome [13].

As for the two groups of players, grandmasters performed better than class-B players and they made less errors. This matches with the findings of Cowley and Byrne [8] that chessmasters tend to evaluate their moves more realistically than novice players. This can be explained by the Chunking Model, according to which the skill of the chess player is based on two factors: the ability to search the tree of moves for a strong move (i.e. success is rated against the subsequent moves derived from it); and the ability to recognize chess patterns quickly and to discover the strong moves [14]. The recognition of chess patterns allows players to save time, which is important to their chance of success, given the limited time available and the number of relevant possibilities through the game. The chess master typically has a huge quantity of large chunks in his Long Term Memory (LTM), therefore he is able to to identify the strong moves based on the positions viewed on the chessboard [14].

These findings highlight the need for continued research on chess personalities in virtual environments. Further investigations to studies of competition between virtual humans of different personalities might help researchers identify how players of different personalities can perform against others who vary in their chess skill. For example, one approach can be via designing a chess software to assess the performance of a chess player against different personalities in the community and provide a feedback on the weakness points and how they can be addressed. In addition, chess software designers could consider building a software which detects chess personality based on chess opponents and then suggesting different virtual opponents based on the personality and not just the rating.

The findings in this research can be beneficial to design virtual humans to assist in chess training. For example, research indicated the power of virtual humans in assisting students in learning topics in different areas such as medical education [1]. Virtual environments can also play an educational role in chess itself, by utilizing virtual humans in helping chess students gain many topics depending on the shortcomings they have. Virtual players can also be used to assess chess players and get a history about them after they play against players of different personalities. For example, the focus of a new research direction could be identifying the style of chess players while they play against different chess humans. This makes it mandatory to analyze more personalities to be used by chess players to identify the best training techniques.

6 Conclusion

This paper has explored different virtual chess players and how they perform when they play against each other. In this research, the researcher chose two virtual grandmasters and three class-B virtual players. The findings show that the attacker personality tends to make less errors than a defensive personality when playing against different class-B players. In addition, the games are longer when playing against an attacker personality.

The results showed that class-B players who are strong at either the opening or endgame perform better than players who are balanced when playing against a grandmaster with attacking or defensive style. In addition the number of moves is the least when playing against a balanced player.

This research allows us to gain a deeper understanding of different chess personalities, and thus to further understand the psychology of competition between different personalities. Understanding chess personalities enables future research to predict chess results based on the personality of the players. A future topic of research could examine the physiology of different chess personalities, just as this study examined the psychological aspects of those personalities.

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