Conference Website: http://taai2015.nutn.edu.tw/
Competition Website: http://oase.nutn.edu.tw/TAAI2015/

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IEEE CIS ETTC Task Force on Emerging Technologies for Computer Go
### Content

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Short Description

- Description

The technique of Monte Carlo Tree Search (MCTS) has revolutionized the field of computer game-playing, and is starting to have an impact in other search and optimization domains as well. In past decades, the dominant paradigm in game algorithms was alpha-beta search. This technique, with many refinements and game-specific engineering, lead to breakthrough performances in classic board games such as chess, checkers and Othello. After Deep Blue’s famous victory over Kasparov in 1996, some of the research focus shifted to games where alpha-beta search was not sufficient. Most prominent among these games was the ancient Asian game of Go. During the last few years, the use of MCTS techniques in Computer Go has really taken off, but the groundwork was laid much earlier. In 1990, Abramson proposed to model the expected outcome of a game by averaging the results of many random games. In 1993, Bruegmann proposed Monte-Carlo techniques for Go using almost random games, and developed the refinement he termed all-moves-as-first (AMAF). Ten years later, a group of French researchers working with Bruno Bouzy took up the idea. Bouzy’s Indigo program used Monte-Carlo simulation to decide between the top moves proposed by a classical knowledge-based Go engine. Remi Coulom’s Crazy Stone was the first to add the crucial second element, a selective game tree search controlled by the results of the simulations. he last piece of the puzzle was the Upper-Confidence Tree (UCT) algorithm of Kocsis and Szepesvari, which applied ideas from the theory of multi-armed bandits to the problem of how to selectively grow a game tree. Gelly and Wang developed the first version of MoGo, which among other innovations combined Coulom’s ideas, the UCT algorithm, and pattern-directed simulations. AMAF was revived and extended in Gelly and Silver’s Rapid Action Value Estimate (RAVE), which computes AMAF statistics in all nodes of the UCT tree. Rapid progress in applying knowledge and parallelizing the search followed. Today, programs such as MoGo/MoGoTW, Crazy Stone, Fuego, Many Faces of Go, and Zen have achieved a level of play that seemed unthinkable only a decade ago. These programs are now competitive at a professional level for 9 x9 Go and amateur Dan strength on 19x19.

One measure of success is competitions. In Go, Monte-Carlo programs now completely dominate classical programs on all board sizes (though no one has tried boards larger than 19x19). Monte-Carlo programs have achieved considerable success in play against humans. An early sign of things to come was a series of games on a 7x7 board between Crazy Stone and professional 5th Dan Guo Juan. Crazy Stone demonstrated almost perfect play. Since 2008, National University of Tainan (NUTN) in Taiwan and other academic organizations have hosted or organized several human vs. computer Go-related events, including the 2008 Computational Intelligence Forum & World 9x9 Computer Go Championship, and 2009 Invited Games for MoGo vs. Taiwan Professional Go Players (Taiwan Open 2009). Besides, the FUZZ-IEEE 2009: Panel, Invited Sessions, and Human vs. Computer Go Competition was held at the 2009 International Conference on Fuzzy Systems in Aug. 2009. This event was the first human vs. computer Go competition hosted by the IEEE Computational Intelligence Society (CIS) at the IEEE CIS flag conference. In 2010, MoGo and Many Faces of Go achieved wins against strong amateur players on 13x13 with only two handicap stones. On the full 19x19 board, programs have racked up a number of wins (but still a lot more losses) on 6 and 7 handicap stones against top professional Go players; also Zen recently won with handicap 4 against Masaki Takemiya 9p. Also, computer Go Programs have won both as White and Black against top players in 9x9 game.

In April 2011, MoGoTW broke a new world record by winning the first 13x13 game against the 5th Dan professional Go player with handicap 3 and reversed komi of 3.5. It also won 3 out of 4 games of Blind Go in 9x9. In June 2011, in the three-day completion held at FUZZ-IEEE 2011, there are four programs, including MoGoTW, Many Faces of Go, Fuego, and Zen, invited to join this competition, and more than ten invited professional Go players accept the challenge, including Chun-Hsun Chou (9P), Ping-Chiang Chou (5P), Joanne Missingham (5P), and Kai-Hsin Chang (4P). The computer Go program Zen from Japan won each competition even playing 19x19 game with Chun-Hsun Chou (9P) with handicap 6, showing that the level of computer Go programs in 19x19 game is estimated at 4D. Also, Many Faces of Go and Zen also won against a 5P Go player in 13x13, with handicap 2 and komi 3.5, improving the April's results by MoGoTW by one stone. In addition, MoGoTW also won all of twenty 7x7 games under a specific komi, that is, setting komi 9.5 and 8.5 as MoGoTW is White and Black, respectively, suggesting that the perfect play is a draw with komi 9. MoGoTW with the adaptive learning ability was first played with the amateur Go players from kyu level to
dan level in Taiwan, on May 6 and May 27, 2012. Estimating the level of an opponent is useful for choosing the right strength of an opponent and for attributing relevant ranks to players. We estimate the relation between the strength of a player and the number of simulations needed for a MCTS to have the same strength. In addition, we also play against many players in the same time, and try to estimate their strength.

In June 2012, Human vs. Computer Go Competition @ IEEE WCCI 2012 saw physiological measurements for testing cognitive science on the game of Go [11]. The game results show that MoGoTW has outperformed humans in 7x7 Go, making no mistake whereas humans, including one 6P player, did mistakes. Humans are still strong in front of computers in 9x9 Go with komi 7. In June 2011, computers won four 13x13 games out of 8 against professional players with H2 and 3.5 komi (i.e. handicap roughly 1.5), the best performance so far [10]. For 13x13 kill-all Go, in Tainan in 2011, MoGoTW could win as White with H8 against Ping-Chiang Chou (5P), which is seemingly the best performance so far. For 19x19, there are still 4 handicap stones, giving to the program an advantage in each corner, so professional Go players mentioned that switching to handicap 3 is a huge challenge. Level assessment in Go shows that our artificial player is also able to analyze the strength of strong players. Importantly, along with this ability to evaluate the strength of humans, the computer can adaptively adjust its strength to the opponent, in order to increase entertainment, which is helpful for motivating children to learn. With the collected physiological signals, it will be feasible to analyze game-level statistics to understand the variance of strategies employed by the human and computer in each game [11].

Classical rankings (1 Dan, 2 Dan, ...) are integers, leading to a rather imprecise estimate of the opponent’s strengths. Therefore, a sample of games played against a computer are used to estimate the human’s strength [12]. In order to increase the precision, the strength of the computer is adapted from one move to the next by increasing or decreasing the computational power based on the current situation and the result of games. The human can decide some specific conditions, such as komi and board size. In [12], type fuzzy sets (T2 FSs) with parameters are optimized by a genetic algorithm for estimating the rank in a stable manner, independently of the board size. More precisely, an adaptive Monte Carlo Tree Search (MCTS) estimates the number of simulations, corresponding to the strength of its opponents. In FUZZ-IEEE 2013 held in India, July 2013, professional and amateur Go players were invited to play with computer Go programs, including MoGoTW with adaptive learning (Taiwan / France), Coldmilk (Taiwan), Zen (Japan), and Many Faces of Go (USA) to analyze the human’s thinking behavior and computer Go program’s computational & machine-learning ability. Additionally, domain experts were interested in discussing over how to combine machine learning with fuzzy sets to construct adaptive learning to assess Go player’s rank.

In 2015, Human vs. Computer Go Competition (7th years) was held as a competition event during IEEE International Conference on Fuzzy Systems 2015 (FUZZ-IEEE 2015). One professional player Ping-Chiang Chou (Pro 6 Dan) and four strong amateur Go players Shi-Jim Yen, Ching-Nung Lin, Wen-Chih Chen (6 Dan), and Francesco Marigo (4 Dan) compete with the world best Go program (Zen) and other two strong Go bots (CGI and Jimmy) from two countries. As a result, there exists a significant gap between human and bots. Since 2013, the progress of computer Go is bounded as four handicaps against with professional Go players. Computation based searching algorithm does not improve as scaling up to thousands of cores. On the contrary, pattern-based knowledge interpreting becomes mainstream. How to translate millions of patterns to accurate categories plays an important role for future improvement. The professional Go player beat the world strongest program two games with four handicaps easily, but lost when the handicap increased to five. Also, this program won a strong amateur Go player as score 2:1 which is similar to the event held in FUZZ-IEEE 2013. The game results held in IEEE CIG 2015 (Tainan, Taiwan) showed that the computer Go programs’ strength has been advanced to 19x19 and maybe computer Go programs will perform better than human about ten years later. However, from the viewpoint of the professional Go players, it still has a lot of difficulties in winning the human for the computer Go program.

- **Human**
- Taiwanese Professional Go Players
  - Yen-Chun Wang (6D)
  - Bo-Yuan Hsiao (6D)
• **Computer Go Program**
  – CGI (Taiwan)

• **Reference**


Web Information

- **Website**
  http://oase.nutn.edu.tw/TAAI2015/

- **Home Page**

The technique of Monte Carlo Tree Search (MCTS) has revolutionized the field of computer game-playing, and is starting to have an impact in other search and optimization domains as well. In past decades, the dominant paradigm in game algorithms was alpha-beta search. This technique, with many optimizations and game-specific engineering, lead to breakthrough performances in classic board games such as chess, checkers and Othello. After Deep Blue's famous victory over Kasparov in 1996, some of the research focus shifted to games where alpha-beta search was not sufficient. Most prominent among these games was the ancient Asian game of Go. During the last few years, the use of MCTS techniques in Computer Go has really taken off, but the groundwork was laid much earlier. In 1993, Blum proposed a classical knowledge-based Go engine. Haih Cai's Crazy Stone was the first to add the crucial second element, a selective game tree search controlled by the results of the simulations. The last piece of the puzzle was the Upper-Confidence Tree (UCT) algorithm of Kocsis and Szepesvár, which applied ideas from the theory of multi-armed bandits to the problem of how to selectively grow a game tree. Gelly and Wang developed the first version of MoGo, which among other innovations combined Coulom's ideas, the UCT algorithm, and pattern-directed simulations. AMAF was released and extended in Gelly and Silver's Rapid Action Value Estimate (RAVE) which computes AMAF statistics in all nodes of the UCT tree. Rapid progress in applying knowledge and parallelizing the search followed. Today, programs such as MoShiMoGo10TW, Crazy Stone, Fuugo, Many Faces of Go, and Zen have achieved a level of play that seemed unthinkable only a decade ago. These programs are now competitive at a professional level for 9 x 9 Go and amateur Dan strength on 19x19.
• Hosts, Co-organizers, and Co-sponsors
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National Chiao Tung University, Taiwan  
Email: icwu@cs.nctu.edu.tw
# Program

**November 22, 2015 (GMT + 8)**

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<th>Time</th>
<th>Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>08:30-09:00</td>
<td>Opening</td>
</tr>
<tr>
<td>09:00-10:30</td>
<td><strong>Human vs. Computer Go Competition #1 (19x19 Game / 45 minutes per side)</strong>&lt;br&gt;#1-1: Yen-Chun Wang (6D, White, H2) vs. CGI (Black, Komi 0.5)</td>
</tr>
<tr>
<td>10:30-12:00</td>
<td><strong>Human vs. Computer Go Competition #2 (19x19 Game / 45 minutes per side)</strong>&lt;br&gt;#2-1: Bo-Yuan Hsiao (6D, White, H2) vs. CGI (Black, Komi 0.5)</td>
</tr>
<tr>
<td>12:00-12:30</td>
<td>Award and Closing</td>
</tr>
</tbody>
</table>

- CGI is developed by CGI Lab, National Chiao Tung University (NCTU), Taiwan.
## Invited Go Players Introduction

<table>
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<th>Go Players</th>
<th>Rank</th>
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<th>Introduction</th>
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<tr>
<td>Yen-Chun Wang</td>
<td>6D</td>
<td>Taiwan</td>
<td><strong>Yen-Chun Wang</strong> was a 6D amateur Go player.</td>
</tr>
<tr>
<td>Bo-Yuan Hsiao</td>
<td>6D</td>
<td>Taiwan</td>
<td><strong>Bo-Yuan Hsiao</strong> was advanced to 6D in 2006 and won the champion of NCGC (National College Go Contest) team competition in 2013.</td>
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Computer Go Programs Introduction

- **Computer Go Program**

<table>
<thead>
<tr>
<th>Name</th>
<th>Country</th>
<th>Introduction</th>
</tr>
</thead>
</table>
| CGI Go Intelligence (CGI) | Taiwan  | • Developers: Ti-Rong Wu, Ting-Fi Liao, Guan-Wen Chen, Chung-Chin Shih, Li-Cheng Lan, Ting-Chu Ho, and I-Chen Wu.  
|                           |         | • Algorithmic Principles: Monte-Carlo Tree Search with RAVE, large-pattern by machine learning, and dynamic komi.  
|                           |         | • Features: CGI uses the framework of Amigo, mainly including parallel processing. Amigo designed by Liao (as his thesis) has a general MCTS framework for all games. |

- **Machine Specification**

<table>
<thead>
<tr>
<th>Name</th>
<th>Country</th>
<th>Machine Spec</th>
</tr>
</thead>
<tbody>
<tr>
<td>CGI</td>
<td>Taiwan</td>
<td>8 x 3 x AMD Opteron 6174/2.2 GHz (ALPS system by Acer)</td>
</tr>
</tbody>
</table>
Taiwan Open 2009 on CNN-iReport

Website
Taiwan Open 2009: http://go.nutn.edu.tw/2009/
ON CNN-iReport: http://www.ireport.com/docs/DOC-214010

Content
The game of Go is one of the last board game where the strongest humans are still able to easily win against artificial intelligence. But researchers have discovered new performing algorithms and computers are catching up really fast. The Taiwan Open 2009 was held in Tainan Taiwan between the tenth and thirteenth of February. On the first two days of the event, the Go program MoGo made two new world records by winning a 19 by 19 game with 7 handicap stones against the 9P professional Go player Jun-Xun Zhou and a 19 by 19 game with 6 handicap stones against the 1P professional Go player Li-Chen Chien. If computers continue to improve at this rate, one more human stronghold may fall in front of machines in less than 10 years.

Arpad Rimmel reports on National University of Tainan (NUTN), Taiwan, on Feb. 14, 2009.
Rules

1. Basic Rules
   • 19×19 Game: 45 minutes per side, Komi 0.5, Chinese rules (90 minutes per game)

2. Informal Outline
   • Chinese Rules
     – area scoring,
     – suicide is illegal,
     – basic ko + long cycle rule (no superko!).
   • 19×19 Go
     – Each program should complete its moves for 19×19 Go in 45 minutes.
     – In case of a dispute where each program has played at least 125 moves in 45 minutes the result is decided by the tournament director. If only one program has not played at least 125 moves in 45 minutes that program loses immediately.

3. Rules
   Important: Although we attempt to be as precise as possible, we cannot rule out that disputes arise due to unforeseen events that are not (adequately) covered by this rules text. When this happen all participants are expected to behave in a sportsmanlike manner and accept the decision by the tournament director (TD), who may use any means at his discretion to come to a fair decision.
   • The Board
     The game of Go is played by two programs, Black and White, on a rectangular grid of horizontal and vertical lines (9×9 or 19×19). Each intersection of the grid is colored black if it contains a black stone, white if it contains a white stone, or empty if it contains no stone. Initially the board is empty.
   • The Move
     One program uses black stones, the other white stones. The program with the black stones starts the game. The programs move alternately. A move is either a play of a stone on an empty intersection, or a pass. Instead of moving, at any point during the game a program, or its operator, may resign, in which case the game ends as a win for the opponent.
   • Connectivity and Liberties
     Two intersections are adjacent if they have a line but no intersection between them. Two adjacent intersections are connected if they have the same color. Two non-adjacent intersections are connected if there is a path along lines of adjacent intersections of their color between them. For an intersection, the intersection and all connected intersections of the same color form a block. The adjacent empty intersections of a block are called liberties.
   • Capture
     A block is captured when the opponent plays a (legal) move on the block’s last liberty. Captured blocks are removed from the grid; the intersections are colored empty.
   • Illegal Moves
     Suicide: A play that does not capture any block and leaves its own block without a liberty is illegal.
     Ko: A play may not capture a single stone if this stone was played to capture a single stone in the last preceding play.
   • Long Cycle Rule
     A board position is defined by the coloring of the grid’s intersections directly after play and any consequent removals. If a play recreates a previous board position then exceptionally and immediately the game ends and is scored, based on an analysis of all moves played since the moment just after the first occurrence until the moment just after the last occurrence, as follows:
     – If between the two occurrences the difference in number of captured black and white stones is not zero, then the program that captured the most stones of the opposing color wins the game.
     – If between the two occurrences the difference in number of captured black and white stones is zero, then the game ends as a draw.
   • Scoring
     Each black or white intersection counts as a point for its respective color. Each empty intersection
which is part of an empty block adjacent only to intersections of one color counts as a point for that adjacent color.

The score is determined according to KGS (http://www.gokgs.com/) scoring rules.

- **References**
  


**T2FS-Based Adaptive Linguistic Assessment System for Semantic Analysis and Human Performance Evaluation on Game of Go**

**Chang-Shing Lee, Senior Member, IEEE, Mei-Hui Wang, Meng-Then Wu, Member, IEEE, Olivier Teytaud, and Shi-Jin Yen, Senior Member, IEEE.**

**Abstract**—The game of Go is a board game with a long history that is much more complex than chess. The uncertainties of this game will be higher when the board size gets bigger. For evaluating the human performance on Go games, one could be advanced to a higher rank based on the number of winning games via a formal human against human competition. However, a human Go player’s performance could be influenced by factors such as the on-the-spot environment, as well as physical and mental situations of the day, which causes difficulty and uncertainty in certifying the human’s rank. Thanks to a sample of one player’s games, evaluating his/her strengths by classical models such as the Bradley–Terry model is possible. However, due to inhomogeneous game conditions and limited access to archives of games, such estimates can be imprecise. In addition, classical rankings (Dan, 2 Dan, …) are integers, which leads to a rather imprecise estimate of the opponent’s strengths. Therefore, we propose to use a sample of games played against a computer to estimate the human’s strengths. In order to increase the precision, the strength of the computer is adapted from one move to the next by increasing or decreasing the computational power based on the current situation and the result of the games. The human can decide some specific conditions, such as komi and board size. In this paper, we use type-2 fuzzy sets (T2FSs) with parameters optimized by a genetic algorithm for estimating the rank in a stable manner, independently of board size. More precisely, an adaptive Monte Carlo tree search (MCTS) estimates the number of simulations, corresponding to the strength of the opponent. Next, the T2FS-based adaptive linguistic assessment system infers the human performance and presents the results using the linguistic description. The experimental results show that the proposed approach is feasible for application to the adaptive linguistic assessment on a human Go player’s performance.

**Index Terms**—Adaptive assessment, fuzzy markup language (FML), game of Go, ontology, type-2 fuzzy set (T2FS).

I. **INTRODUCTION**

Owing to the prosperity of artificial intelligence (AI) research, many researchers have devoted themselves to challenging humans based on the AI techniques, especially applications to the board games. The game of Go originated from China [1], and it is played by two players; black and white. Two Go players alternatively play their stone at a vacant intersection of the board following the rules of Go. The most common board size for human against human is 19 × 19, and 9 × 9 is also popular for Go beginners. In the end, the player with a bigger territory wins the game [1]. Additionally, Go is regarded as one of the most complex board games because of its high state-space complexity $10^{172}$, game-tree complexity $10^{459}$, and branching factor 250 [2]. Because of this, Go has a high uncertainty especially on a 19 × 19 big-size board.

For evaluating the human performance on Go games, humans could be advanced to a higher rank based on the number of winning games via a formal human against human competition, for example, by winning four out of five games. However, the invited human Go player’s strength might be affected by some factors, such as the on-the-spot environment, physical and mental situations of the day, and game settings; therefore, the Go player’s rank may be with an uncertain possibility. Additionally, one player’s strength may gradually decrease because of getting older or seldom playing with a stronger human. The strength of one about 6D player may be between stronger than 5D and weaker than 7D. Hence, these uncertain factors cause the difficulties and uncertainty in evaluating the rank of one human Go player.

Type-2 fuzzy sets (T2FSs) can model the requirements of a person specification that is reflective of all the experts’ opinions and this can be used to provide a good evaluation for the rank of the Go players. Additionally, the spread of type 2 fuzzy logic systems (T2FLSs) has continuously increased in recent years both in numbers and in the areas of applications. Real-world applications are characterized by high levels of linguistic and numerical uncertainties [3]. In 1973, Zadeh proposed T2FLS as an extension to the ordinary fuzzy sets [50]. T2FS has the ability to capture the uncertainty about membership functions of fuzzy sets [4], [5]. Moreover, T2FLS is used to handle the high uncertainties in the group decision-making process as it can model the uncertainties between expert preferences by using T2FSs [4], [5].

Recently, there exists a variety of real-world T2FLS applications in the business and finance, electrical energy,

Since 2008, National University of Taiwan (NUTN) in Taiwan and other academic organizations have hosted or organized several human vs. computer Go-related events [1, 2, 3, 4, 5] in Taiwan and in IEEE CIS flag conferences, including FUZZ-IEEE 2009, IEEE WCCI 2010, IEEE SSCI 2011, and FUZZ-IEEE 2011. Chun-Hun Chou (99), Ping-Chiang Chou (SP), Joanne Musingham (6P), Shiang-Rong Tsai (6D), Sheng-Shu Chang (6D), and Shi-Jim Yen (6D) were invited to attend the Human vs. Computer Go Competition @ IEEE WCCI 2012 game against Zen; she played a move for chasing Zen (a very suboptimal move, aimed at making the situation difficult) and Zen erroneously resigned, whereas the situation was admittedly a win for Zen. There are still 4 handicap stones, giving to the program an advantage in each corner, so professional Go players mentioned that switching to handicap 3 is a huge challenge. In particular, computers still have weaknesses for combining multiple local fights. Remarkably, Many Faces of Go won as Black with komi 3.5, i.e. roughly a activities for physiological measurements to see if physiological signals are also impacted by various conditions. It is now known that Go is specific in the sense that brain areas involved in playing Go are not exactly the same as those involved in chess, in particular, more spatial reasoning, mental verbalization, and motor control. The design of games was to investigate the current level of strong programs on various board sizes, but also to monitor the human brain and to check the player strength assessment capabilities of Go programs. Australian Broadcasting Cor-

when computer is White and 9.5 when computer is Black). The game results show that MoGoTW won all games which were "easy" for it and won 50% of "hard" games against three 6D players. MoGoTW also won 1 out of 6 games in the hard setting against professional players. However, Joanne Musingham (6P) said that the reason she lost the game is that she is not familiar with 7x7 game, and this lost game is her first 7x7 game. MoGoTW has outperformed humans in 7x7 Go, making no mistake whereas humans, including one 6P

Abstract   The game of Go is considered one of the most complicated games in the world. One Go game is divided into three stages: the opening, the middle, and the ending stages. Millions of people regularly play Go in countries around the world. The game is played by two players. One is White and another is Black. The players alternate placing one of their stones on an empty intersection of a square grid-patterned game board. The player with more territory wins the game. This paper proposes a soft-computing-based emotional expression mechanism and applies it to the game of computer Go to make Go beginners enjoy watching Go game and keep their tension on the game. First, the knowledge base and rule base of the proposed mechanism are defined by following the standards of the fuzzy markup language. The soft-computing mechanism for Go regional alarm level is responsible for showing the inferred regional alarm level to Go beginners. Based on the inferred board situation, the fuzzy inference mechanisms for emotional pleasure and arousal are responsible for inferring the pleasure degree and arousal degree, respectively. An emotional expression mapping mechanism maps the inferred degree of pleasure and degree of arousal into the emotional expression of the eye robot. The protocol transmission mechanism finally sends the pre-defined protocol to the eye robot via universal serial bus interface to make the eye robot express its emotional motion. From the experimental results, it shows that the eye robot can support Go beginners to have fun and retain their tension while watching or playing a game of Go.

Keywords   Soft-computing - Ontology - Fuzzy markup language - Computer Go - Fuzzy inference mechanism - Emotional expression

1 Introduction   According to Werf (2004), Go originated in China and was imported to Japan around the seventh century. Westerners first came into contact with Go in the late sixteenth century. Normally, the weaker player uses black stones and starts the game. Go rules are simple, but it is much more complex than chess (Werf 2004). As the game progresses, the players alternatively place one of their stones on an empty intersection of the game board. The size of the board is $19 \times 19$ in almost all of official games. In the end, the player who controls the most intersections on the board wins the game. According to The International Go Federation (2012), the total number of Go players worldwide is well over 40 million, with the overwhelming majority in East Asia. Nowadays, with the support of the Internet, people are able to play a variety of computer games, including Go, against a human player or against a computer program. The ability of computer programs to play Go has
The Game of Go @ IEEE WCCI 2010

The game of Go originated from China. Around the 7th century, the game was imported to Japan. In the late 16th century, the first Westerner came into contact with Go. There are millions of people that regularly play Go in many countries around the world. Played by two players, Black and White, the stones of their color are placed consecutively on an empty intersection of a square grid. Normally, the weaker player plays Black and starts the game. In the end, the player who controls the most intersections of the board wins the game [1]. Go is a board game that is much more complex than chess. Indeed, the number of possible moves in the game of Go is more important and the size of the tree of possibilities is greater than the number of atoms in the universe [2]. However, despite several decades of artificial intelligence or computational intelligence, there are still no computer Go programs that can challenge a strong professional player in 19 \times 19 games without handicap. This is because Go is a problem with high uncertainty; especially for big board games, like the 19 \times 19 board. Each Go player has his own way of thinking to play with his opponent, and each top professional Go player will take different strategies even though they face the same situation. Thus, in 1997, the IBM’s Deep Blue Supercomputer beat the World Chess Champion, Garry Kasparov, while the game of Go is still one of the last board games where the strongest humans are still able to easily win against computers in big board games [3, 4, 5].

Since 2008, National University of Taiwan (NUTN) in Taiwan and other academic organizations have hosted or organized several human vs. computer Go-related events, including the 2008 Computational Intelligence Forum & World 9 \times 9 Computer Go Championship (http://go.nutn.edu.tw/) [3], and 2009 Invited Games for McGo vs. Taiwan Professional Go Players (Taiwan Open 2009, http://go.nutn.edu.tw/2009/) [4]. Besides, the FUZZ-IEEE 2009: Panel, Invited Sessions, and Human vs. Computer Go Competition (http://eose.nutn.edu.tw/FUZZ_IEEE_2009/) [5] was held at the 2009 International Conference on Fuzzy Systems (FUZZ-IEEE 2009) in Aug. 2009. This event was the first human vs. computer Go competition hosted by the IEEE Computational Intelligence Society (CIS) at the IEEE CIS Bag conference, and Dr. David Fogel (2008–2009 IEEE CIS President) also presented a certificate to the invited Go players to recognize their continued commitment and service to the research and development for computer Go at the banquet. McGoTW was developed based on McGo 4.86 Sessions and the Taiwan (TW) modifications. This was developed jointly with the Taiwanese colleagues for a National Science Council (NSC)-National Research Agency (ANR) research project between Taiwan and France. The 2010 Invited Game for McGoTW vs. Human Go Player (http://go.nutn.edu.tw/2010/) was held at the NUTN, Taiwan, on Mar. 21, 2010 and McGoTW was qualified to award three certificates with 1st Dan (1D), 2D, and 3D level on Apr. 2, 2010.

This human vs. computer Go competition (http://wcc2010.nutn.edu.tw/), organized by the IEEE CIS, 2010 IEEE World Congress on Computational Intelligence (WCCI 2010), IEEE CIS Emergent Technologies Technical Committee, and the National University of Taiwan (NUTN) in Taiwan, was entitled "The Game of Go @ IEEE WCCI 2010", and aims to promote the research and development of AI in the game of Go. The first prize of the competition was given to the team that successfully challenge the human champion's position. The competition was divided into three categories: the 19 \times 19 category, the 9 \times 9 category, and the 5 \times 5 category. The 19 \times 19 category received the most attention, with 16 teams participating. The top three teams were: 1st place: TCC (Taiwan Cherry Choi) team, 2nd place: Team Go (Taiwan), and 3rd place: Team McGo (McGoTW). The competition was successful in promoting AI research and development in the game of Go.
Current Frontiers in Computer Go

Arpad Rimmel, Olivier Teytaud, Chang-Shing Lee, Shi-Jim Yen, Mei-Hui Wang, and Shang-Rong Tsai

Abstract—This paper presents the recent technical advances in Monte Carlo tree search (MCTS) for the game of Go, shows the many similarities and the rare differences between the current best programs, and reports the results of the Computer Go event organized at the 2009 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE2009), in which four main Go programs played against top level humans. We see that in 9 x 9, computers are very close to the best human level, and can be improved easily for the opening book; whereas in 19 x 19, handicap 7 is not enough for the computers to win against top level professional players, due to some clearly understood (but not solved) weaknesses of the current algorithms. Applications far from the game of Go are also cited. Importantly, the first ever win of a computer against a 9th Dan professional player in 9 x 9 Go occurred in this event.

Index Terms—Game of Go, Monte Carlo tree search (MCTS), upper confidence.

I. INTRODUCTION

The game of Go is one of the main challenges in artificial intelligence. In particular, it is much harder than Chess, in spite of the fact that it is fully observable and has very intuitive rules.

Currently, the best algorithms are based on Monte Carlo tree search (MCTS) [1]-[3]: they reach the professional level in 9 x 9 Go (the smallest, simplest form) and form amateur level in 19 x 19 Go.

During the 2009 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE2009), in Jeju Island, games were played between four of the current best programs against a top level professional player and a high-level amateur. We will use the results of the different games in order to summarize the state of the MCTS algorithms, the main differences between the programs, and the current limitations of the algorithm.

1) History of Computer Go: The ranks in the game of Go are ordered by decreasing Kyu, increasing Dan, and then increasing professional Dans: 20 Kyu is the lowest level, 19K, 18K, ...
and 1; 1Dan, 2D, 3D, ..., and 7D; the first professional Dan 1P is then considered as nearly equivalent to 7D, followed by 2P, 3P, 4P, ..., and 9P. The title "top pro" is given to professional players who recently won at least one major tournament.

2) 9 x 9 Go: In 2007, MoGo won the first ever game against a pro, Guo Jun 5P, in 9 x 9, in a blitz game (10 min per side). This was done a second time, with long time settings, in 2008, also by MoGo and against Catalin Taramu 5P. The only wins as black against a pro were realized by MoGo against Catalin Taramu (5P) in Paris (France, 2008) and the win against C.-H. Chou (Taipei, 2009).

3) 19 x 19 Go: In 1998, M. Müller could win against Many Faces Of Go, one of the top programs at that time, in spite of 29 handicap stones, an incredibly big handicap, so big that it does not make sense for human players. In 2008, MoGo won the first ever game in 19 x 19 against a pro, K. Muyongwan, 8P, in Portland; however, this was with the largest usually accepted handicap, i.e., nine stones. CrazyStone then won against a pro with handicap 8 and 7 stones in Tokyo (Achib Kaci 4P, in 2008); finally, MoGo won with handicap 7 against a top level human player, C.-H. Chou (9P and winner of the famous LG Cup in 2007), and against a 1P player with handicap 6 in Taiwan (Taiwan, 2009).

During FUZZ-IEEE2009 there was the first win of a computer program (the Canadian program Puego) against a 9P player in 9 x 9 as white. On the other hand, none of the programs could win against C.-H. Chou in 19 x 19, in spite of the handicap 7, showing that winning with handicap 7 against a top level player is still almost impossible for computers, in spite of his recent win by MoGo a few months earlier with handicap 7. Also, during FUZZ-IEEE2009, no program could win as black in 9 x 9 Go with komi 7.5 against the top pro.


S.-S. Chang is a 6D amateur from Taiwan.

5) Technical Terms From the Game of Go: In this section, we define several Go terms. A group is a connected set of stones (for 4-connectivity). A liberty is an empty location, next to a group; a group is captured when it has no more liberties; it is then removed from the board. A group is termed dead when it is definitely going to be captured. An atari is a situation in which a player plays a move in the liberties of a group, so that only one liberty remains. A renju is a situation in which two groups have common liberties and none of the players can play in these liberties without being in self-atari. The komi is the number of points given to white, as a compensation for playing second. The handicap in a game is a number of stones; with handicap N, the black player plays N...
An Ontology-based Fuzzy Inference System for Computer Go Applications

Chang-Shing Lee, Mei-Hui Wang, Shi-Jim Yen, Yu-Jen Chen, Cheng-Wei Chou, Guillaume Chaslot, Jean-Baptiste Hooock, Arpad Rimmel, and Hassen Doghmen

Abstract

In order to stimulate the development and research in computer Go, several Taiwanese Go players were invited to play against some famous computer Go programs. Those competitions revealed that the ontology model for Go game might resolve problems happened in the competitions. Therefore, this paper presents a Go game record ontology and Go board ontology schemes. An ontology-based fuzzy inference system is also developed to provide the regional alarm level for a Go beginner or a computer Go program in order to place the stone at the much more appropriate position. Experimental results indicate that the proposed approach is feasible for computer Go application. Hopefully, advances in the intelligent agent and the ontology model can provide a significant amount of knowledge to make a progress in computer Go program and achieve as much as computer chess or Chinese chess in the future.

Keywords: Computer Go, Fuzzy Inference, Knowledge Management, Ontology.

1. Introduction

As Go remains a challenge for computer science research [1], Monte Carlo methods are highly promising for such applications, especially for small versions of the game such as 9×9 games. Worf et al. [2] devised a search-based approach for playing Go on small boards.

Bouzy and Cazenave [3] presented an AI-oriented survey of computer Go. Martin Müller won despite 29 handicap stones against the computer Go program Many Faces of Go [4]. The computer Go program MuGo achieved unprecedented impressive results in 19×19 game by winning with a handicap of six and seven stones against a 2P and a 9P Go player, respectively, in Taiwan Open 2009 [15]. The computer Go program Fuego won a 9×9 game as White against the 9P Go player in August 2009 [18]. The latest world record involved the computer Go program MuGoTW winning a 9×9 game as Black against the 9P Go player in October 2009 (http://mogetw.nutn.edu.tw), which is extremely more difficult for the computer Go program to win a top professional Go player as Black than as White.

Knowledge refers to relevant and actionable information that is based on an individual’s experience [5]. Although all knowledge workers share certain characteristic activities, annotated data is obtained within a framework or ontology [6]. As a highly effective means of sharing knowledge and representing information and its semantics [7], ontology is a conceptualization of a real world domain in a human understandable, machine-readable format that consists of entities, attributes, relationships, and axioms [8]. Moreover, ontology mediation allows us to combine knowledge from the ontologies [6]. For instance, in addition to proposing a fuzzy ontology scheme for summarizing news [9], Lee et al. also developed an ontology-based intelligent decision support agent for project monitoring and control (PMCC) process area of the capability maturity model integration (CMMI) [10]. Reformat and Ly [7] devised an ontology-based approach to provide a rich environment for expressing different information types, including perceptions.

Monte Carlo Tree Search (MCTS)-based computer Go is an important milestone for computer Go development. Minimax and alpha-beta searches are the conventional approaches adopted in computer games. However, in Go, even after pruning by patterns or rules, these approaches are clearly outperformed by MCTS [15]. Bruggmann developed an original evaluation function based on Monte Carlo exploration [11]. The All-Moves-As-First (AMAF) value of a move enhances the Monte Carlo evaluation by using statistics on permutations of games. In the MCTS setting, AMAF values are usually called...

**THE IEEE SSCI 2011 HUMAN VS. COMPUTER-GO COMPETITION**

Shi-Jim Yen, Cheng-Wei Chou, Chang-Shing Lee, Hassen Doghmen, and Olivier Teytaud

Hualien, Taipei, Taiwan
Paris, France

A Human vs. Computer Go Competition was held as a part of the IEEE Symposium Series on Computational Intelligence 2011 (IEEE SSCI 2011). The competition took place from April 13th to 14th 2011 at Paris, France. There were several games in this competition, including 13x13 Go, 19x19 Go, Blind Go, and Random Go games. This report focuses on 13x13 Go and 19x19 Go. For Blind Go and Random Go, please refer to the report by Yen et al. (2011). The human participants Chun-Hsun Chou and Ping-Chiang Chou are brothers. They both are professional Go Players. Table 1 shows information on the human participants. Table 2 shows information of the two computer Go programs, MOGO and PACHI.

<table>
<thead>
<tr>
<th>Name</th>
<th>Rank</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chun-Hsun Chou</td>
<td>9-Dan (Pro)</td>
<td>Winner of 2007 LG Cup, the contest offering the largest reward in the world every year</td>
</tr>
<tr>
<td>Ping-Chiang Chou</td>
<td>5-Dan (Pro)</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: List of human participants.

<table>
<thead>
<tr>
<th>Program</th>
<th>Country</th>
<th>Authors</th>
<th>Machine Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>MOGO</td>
<td>France</td>
<td>Many authors; see <a href="http://www.lri.fr/~teytaud/mogochess.html">http://www.lri.fr/~teytaud/mogochess.html</a></td>
<td>The Grid5000 grid (<a href="http://www.grid5000.fr">www.grid5000.fr</a>)</td>
</tr>
<tr>
<td>PACHI</td>
<td>Czech Republic</td>
<td>Petr Baudis, Jean-loup Gailly</td>
<td>A cluster (64 machines, 20 cores each)</td>
</tr>
</tbody>
</table>

Table 2: Information of the Go-program participants.

<table>
<thead>
<tr>
<th>Name</th>
<th>Handicap</th>
<th>MOGO</th>
<th>PACHI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chun-Hsun Chou</td>
<td>H2</td>
<td>W+R</td>
<td>B+R</td>
</tr>
<tr>
<td>H2.5</td>
<td>W+R</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ping-Chiang Chou</td>
<td>H2.5</td>
<td>B+0.5</td>
<td>W+R</td>
</tr>
</tbody>
</table>

Table 3: The result of the 13x13 games

<table>
<thead>
<tr>
<th>Name</th>
<th>Handicap</th>
<th>MOGO</th>
<th>PACHI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chun-Hsun Chou</td>
<td>H7</td>
<td>W+R</td>
<td>B+R</td>
</tr>
<tr>
<td>Ping-Chiang Chou</td>
<td>H6</td>
<td>W+R</td>
<td>W+R</td>
</tr>
</tbody>
</table>

Table 4: The result of the 19x19 games

The games were played under Chinese Go rules. In 13x13 Go, there are two different handicaps: H2 and H2.5. H2.5 means handicap 3 with komi 3.5. The thinking time of 13x13 Go was 30 minutes per side. Table 3 shows the result of the 13x13 games. In 19x19 Go, both MOGO and PACHI played both H7 and H6 games. The thinking time of 19x19 Go was 45 minutes per side. PACHI won one H7 game by killing a big group of the winner of 2007 LG Cup, Chun-Hsun Chou. Chou 9P said that PACHI played in pro-level for killing a big group. Although computer Go programs can beat the strongest human in 9x9 Go (Billouet et al., 2009; Wang et al., 2010; Yen, Olivier and Lee, 2009), but the gap between computer Go programs and human professional Go players is still big in 19x19 Go (Lee et al., 2011). The 13x13 Go was first held in a Human vs. Computer Go Competition. It may be a next target for Computer Go to beat the top pro in the near future.

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Chang-Shiing Lee and Mei-Hui Wang
National University of Taiwan, TAIWAN

Intelligent Agents for the Game of Go

I. Introduction

Monte-Carlo Tree Search (MCTS) was recently proposed [1, 2, 3] for decision making in discrete time control problems. It was applied very efficiently to games [4, 5, 6, 7, 8] and also to planning problems and fundamental artificial intelligence tasks [9, 10]. It clearly outperformed alpha-beta techniques when there was no human expertise easy to encode in a value function. In this section, we will describe MCTS and how it allowed great improvements for computer Go. Section II shows the strengths and limitations of MCTS, and in particular, the lack of learning. There are, however, a few known techniques for introducing learning: Rapid-Action Value Estimate (RAVE) and learned patterns (both well-known now, and discussed below); our focus is on more recent and less widely-known learning techniques introduced in MCTS. The next two sections will show these less standard applications of supervised learning within MCTS: Section III will show how to use past games for improving future games, and section IV will show the inclusion of learning inside a given MCTS run. Section V will be the conclusion.

The technique of Monte Carlo tree search (MCTS) has revolutionized the field of computer game playing, and is starting to have an impact in other search and optimization domains as well. In past decades, the dominant paradigm in game algorithms was alpha–beta search. This technique, with many refinements and game-specific engineering, led to breakthrough performances in classic board games such as Chess, Checkers, and Othello. After Deep Blue's famous victory over Kasparov in 1996, some of the research focus shifted to games where alpha–beta search was not sufficient. Most prominent among these games was the ancient Asian game of Go. Despite much effort, progress remained slow for another decade. During the last few years, the use of MCTS techniques in Computer Go has really taken off, and the groundwork was laid much earlier. In 1990,Abramson [1] proposed to model the expected outcome of a game by averaging the results of many random games. In 1993, Brügmann [2] proposed Monte Carlo techniques for Go using almost random games, and developed the refinement he termed all-moves-as-first (AMAF). Ten years later, a group of French researchers working with Bouzy and Cazenave took up the idea [3]. Bouzy's Indigo program used Monte Carlo simulation to decide between the top moves proposed by a classical knowledge-based Go engine.

Coulom's Crazy Stone [4] was the first to add the crucial second element, a selective game tree search controlled by the results of the simulations. The last piece of the puzzle was the upper confidence tree (UCT) algorithm of Kocsis and Szepesvari [5], which applied ideas from the field of multiarmed bandits to the problem of how to selectively grow a game tree. Gelly and Wang developed the first version of MoGo [6], which among other innovations combined Coulom's ideas, the UCT algorithm, and pattern-directed simulations. AMAF was revived and extended in Gelly and Silver's rapid action value estimate (RAVE), which computes AMAF statistics in all nodes of the UCT tree. Rapid progress in applying knowledge and parallelizing the search followed. Today, programs such as MoGo/MoGoTW, Crazy Stone, Fuego, Many Faces of Go, and Zen have achieved a level of play that seemed unthinkable only a decade ago. These programs are now competitive at a professional level for 9 × 9 Go and amateur Dan strength on 19 × 19 [7].

One measure of success is competitions. In Go, Monte Carlo programs now completely dominate classical programs on all board sizes (though no one has tried boards larger than 19 × 19). Monte Carlo programs have achieved considerable success in play against humans. An early sign of things to come was a series of games on a 7 × 7 board between Crazy Stone and professional 5th Dan Guo Juan. Crazy Stone demonstrated almost perfect play. In 2009, a series of matches held on a 9 × 9 board, culminated in program wins playing as both white (the easier color) with Fuego and black with MoGo/MoGoTW against the top level professional Go player Chun-Hsun Chou. In 2010, MoGo and Many Faces of Go achieved wins against strong amateur players on 13 × 13 with only two handicap stones. On the full 19 × 19 board, programs have racked up a number of wins (but still a lot more losses) on six and seven handicap stones against top professional Go players [8, 9].

Besides rapid progress in Go, the most exciting recent developments in MCTS have shown an ever increasing array of applications. In games such as Hex, Havannah, and Lines of Action, MCTS is the state of the art. MCTS can play very well even with little knowledge about the game as evidenced by its success in general game playing. In areas as diverse as energy optimization problems, tuning of libraries, domain-independent planning, and solving Markov decision processes (MDPs), techniques inspired by MCTS are rapidly being developed and applied. However, current MCTS techniques do not work well for all games or all search problems. This poses some interesting questions. When and why does it succeed and fail? How can it be extended to new applications where it does not work yet? How best may it be combined with other approaches such as classical minimax search and knowledge-based methods?

The purpose of this Special Issue on Monte Carlo Techniques and Computer Go is to publish high-quality papers reporting the latest research covering the theory and practice of those and other methods applied to Go and other games. The special issue received eighteen paper submissions, of which eight have been accepted. These papers cover Go, Lines of Action, Hex, single-player general game playing, parallelization in Go, and analyzing game records using Monte Carlo techniques.

The first paper, “Current frontiers in Computer Go” by Rimmel et al., presents an overview of the state of the art in Computer Go by some of the current members of the MoGo project, shows the many similarities and the rare differences between the current best programs, and reports the results of the Computer Go event organized at the 2009 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2009). Importantly, the first ever win of a computer against a 9th Dan professional player in 9 × 9 Go occurred at this event.

The second paper, “Monte Carlo tree search in Lines of Action” of Winands et al., presents a MCTS-based program for playing the game Lines of Action (LOA). With the improved MCTS variant, the proposed program is able to outperform even the world’s strongest alpha–beta-based LOA program. This is an important milestone for MCTS because the traditional game-
2010 INVITED GAME FOR MOGOTW VS. HUMAN GO PLAYER IN TAIWAN

Mei-Hui Wang, Chang-Shing Lee, Yuan-Liang Wang, Ming-Chi Cheng, Olivier Teytaud, and Shi-Jin Yen

ABSTRACT

This article reports the invited games played in the 2010 Invited Game for MOGOTW vs. Human Go Player, held at National University of Taiwan (NUTN), Taiwan, on Mar. 21, 2010. Twenty-four Go players ranking from 1D(Dan) to 3D were invited to challenge the computer Go program MOGOTW by playing 9 × 9 games to validate if MOGOTW has been reached to 1D, 2D or 3D based on the amateur Taiwanese scale. From the games results, MOGOTW won 23 out of 24 games so that MOGOTW was awarded the 1D, 2D, and 3D certificates, by the Taiwanese Go Association at the Hainong Weiqi Academy on Apr. 2, 2010. In the future, the team members of MOGOTW in both Taiwan and France will continue to improve the weaknesses of MOGOTW to let computer Go achieve as much as computer chess or Chinese chess.

1. INTRODUCTION

Go is one of the most complex board games. It is played regularly by millions of players in many countries around the world. Despite several decades of artificial intelligence, there are still no computer Go programs that can challenge a strong professional player in 19 × 19 games [1]. This is because Go is a problem with high uncertainty, especially for big board games, like 19 × 19 board. Each player has his own thinking way to play with his opponent, and each top professional Go player would take different strategies even though facing the same situation. For the past several years, computer Go has been developing by researchers. In 1998, Martin Müller won despite 29 handicap stones against Many Faces of Go. In 2008, MoGo and CrazyStone won Myung-Wan Kim (8th Dan Pro and winner of the 2008 US Open) and Kaori Aoba (4th Dan Pro, 4P) in 19 × 19 games with handicap 9 and 7 stones, respectively. Since 2008, National University of Taiwan (NUTN) and other organizations have hosted or organized several Go-related events, including the 2008 Computational Intelligence Forum & World 9 × 9 Computer Go Championship (http://go.nutn.edu.tw/) [2], 2009 Invited Games for MoGo vs. Taiwan Professional Go Players (Taiwan Open 2009, http://go.nutn.edu.tw/2009/) [3], and FUZZ-IEEE 2009: Panel, Invited Sessions, and Human vs. Computer Go Competition (http://eese.nutn.edu.tw/ FUZZ_IEEE_2009/) [4].

In Feb. 2009, MoGo won with handicap 7 and 6 stones against Chou-Hsun Chou (9P and winner of the LG Cup 2007) and Li-Chen Chien (1P), respectively, at Taiwan Open 2009. Taiwanese Go players were invited to play with four world's top computer Go programs, including MoGo, Fuego, Zen, and Many Faces of Go at the FUZZ-IEEE 2009: Panel, Invited Sessions, and Human vs. Computer Go Competition, held in Jeju Island, Korea, on Aug. 20–23, 2009. In this event, Fuego won by 2.5 points as White against Chou-Hsun Chou in a 9 × 9 game. The computer Go MOGOTW was developed based on MoGo 4.86 Sessions plus the Taiwan (TW) modifications developed jointly with the Taiwanese colleagues for a National Council Science (NCS)-National Research Agency (ANR) research project between Taiwan and France. In Oct. 2009, MoGoTW also won the first 9 × 9 game against top professional Go player (Chou-Hsun Chou) as Black (http://mogotw.nutn.edu.tw/chinese_result_20091026.htm). Therefore, computer Go Programs have won both as White and Black against top players in 9 × 9 game.

The 2010 Invited Game for MOGOTW vs. Human Go Player (http://go.nutn.edu.tw/2010/) was held at NUTN, Taiwan on Mar. 21, 2010. The age of the 24 invited Go players were from 8 to 13. And, they were divided into three groups according to their dan grade of Go, namely 1D-3D (Dan). Each group had eight children. MOGOTW won all of the games except one game against a 3D Go player. Despite one lost game, MOGOTW was qualified to award three certificates with 1D, 2D, and 3D level on Apr. 2, 2010. It was the first time that the Taiwanese Go association awarded a certificate to a computer Go program. Simultaneously, a ceremony about the cooperative agreement memorandum between NUTN and Taiwan’s National Center for High-Performance Computing (NCHC) in Taiwan was held and four Go players, including a 9P, 1P, 7D, and 6D, were invited to play against MOGOTW. In the end of the games, MOGOTW won 3 out of 7 games. The remainder of this report is as follows. Section 2 describes the game results. Finally, we draw the conclusions in Section 3.
The Computational Intelligence of MoGo Revealed in Taiwan’s Computer Go Tournaments

Chang-Shing Lee, Senior Member, IEEE, Mei-Hui Wang, Guillaume Chaslot, Jean-Baptiste Hoock, Arpad Rimmel, Olivier Teytaud, Shang-Rong Tsai, Shun-Chin Hsu, and Tsung-Fei Hong, Member, IEEE

Abstract—In order to promote computer Go and stimulate further development and research in the field, the event activities, Computational Intelligence Forum and World 9 x 9 Computer Go Championship, were held in Taiwan. This study focuses on the invited games played in the tournament Taiwanese Go Players versus the Computer Program MoGo held at the National University of Taidan (NUTN), Taiwan, Taiwan. Several Taiwanese Go players, including one 9-Dan (9D) professional Go player and eight amateur Go players, were invited by NUTN to play against MoGo from August 26 to October 4, 2008. The MoGo program combines all-moves-as-first (AMAP)/rapid action value estimation (RAVE) values, online “upper confidence tree (UCT)-like” values, offline values extracted from databases, and expert rules. Additionally, four properties of MoGo are analyzed including: 1) the weakness in corners, 2) the scaling over time, 3) the behavior in handicap games, and 4) the main strengths of MoGo in contact fights. The results reveal that MoGo can reach the level of 5 dan (3D) with: 1) good skills for fights, 2) weaknesses in corners, in particular, for “symmetrical” situations, and 3) weaknesses in favorable situations such as handicap games. It is hoped that the advances in AI and computational power will enable considerable progress in the field of computer Go, with the aim of achieving the same levels as computer Chess or Chinese Chess in the future.

Index Terms—Computational intelligence, computer Go, MoGo, Monte Carlo tree search (MCTS)

I. INTRODUCTION

GAMES provide competitive dynamic environments that are ideal for testing computational intelligence theories, architectures, and algorithms [1]. Many studies have identified the developments, challenges, and opportunities for applying computational intelligence methods to games [1]. [2]. Additionally, Go remains an excellent challenge for computer science research; however, Monte Carlo methods have very recently shown significant promise, especially for small versions of the game such as 9 x 9 games. Therefore, the upper confidence tree (UCT) Monte Carlo has considerable potential for application to other games such as Hex, Amazon, and even Shogi [2], [39]. Schaeffer and Henik [38], [39] noted that work on computer games has resulted in advances in numerous computing areas. Many ideas that developed through game-tree search have been applied to other algorithms. For example, the UCT Monte Carlo algorithm may have important applications to control non-player characters (NPCs) in video games such as Quake [1], [2]. Moreover, many studies have applied AI and evolutionary computation to games. For instance, Chellappa and Fogel [3], [4] developed an expert program that plays Checkers without using human expertise or expert knowledge. Messerschmidt and Engelsbrodt [5] developed a competitive learning approach to playing games. Wert et al. [6] presented a search-based approach for playing Go on small boards. Boury and Cazanove [7] presented an AI-oriented survey of computer Go. Togelius et al. [8] applied computational intelligence to racing games. Chen [9] proposed a strategy that maximizes the chance of winning when searching Go game trees. Cusumano et al. [41] advocated the development of adaptive programming as an alternative to current constructive programming techniques, as well as the application of adaptive programming to many domains. Carbone et al. [42] proposed an interactive story authoring technology that offers students on opportunity to successfully construct interactive game stories. Zabavi et al. [40] proposed a new dual search algorithm to improve the chance of reaching a goal fast, meaning that the algorithm does not necessarily visit all states on a solution path.

In Checkers, humans now win a handicap (five to favor the human) to have a chance of winning against top-level programs. In Go, humans are still heavily favored to win. For example, in 1998, Muller won despite 29 handicap stones against Many Faces Of Go [11]. Computer Go has, however, made considerable progress in recent years. Programs are currently competitive at the professional level in 9 x 9 Go, and MoGo has won with an advantage of “only” nine handicap stones against top-level human players in 19 x 19 Go; additionally, CrazyStone won with handichips of eight and seven stones against Kaori Aoba, a Japanese 4th Dan Pro (4P). To strengthen computer Go programs and advocate research, development and application of computer games’ related fields, Cheng Jing Christian University (CJC), National University of Taidan (NUTN), and the Taiwan Association for Artificial Intelligence (TAAI) hosted the 2008 Computational Intelligence
Past Human vs. Computer Go Competition

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Last Updated: November 26, 2015   Program Manual for Human vs. Computer Go Competition @ TAAI 2015 27/34
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