TODO: A Survey of StarCraft AI Techniques

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***Abstract*—TODO: Idea of the paper is: "one-stop guide on what is the state of the art in Starcraft AI". It should help people participating in the competition focus their efforts, and also should help people implementing AI for RTS games in general (e.g. industry). In Gabriel's words "RTS AI problems, Solutions, State-of-the-art, conclude on what's "solved" since [1] and what's not."**

For example, if someone wants to implement a bot, and wonders "how should I do scouting", our paper should provide a summary of the existing techniques, and pointers to know more.

***Index Terms*—Game AI, Real-Time Strategy, Starcraft, Review1**

I. Introduction

SINCE Michael Buro's call for research in RTS games [1], many researchers have answered the call. Specially, AI competitions like the "AIIDE Starcraft AI Competition" have caused many AI techniques to be applied to RTS AI. We will list and classify these approaches, explain their power and their downsides and conclude on what is left to achieve human-level RTS AI.

Motivate the paper, and provide an outline.

Some arguments to use in the motivation could be that games are a good application to motivate novel AI research (as has been happening throughout the history of AI), and that techniques and algorithms developed for RTS games, in addition to be useful and relevant to the game industry, have broader application to other areas.

Reiterate that the goal of this paper is to provide a one-stop guide on what is the state of the art in Starcraft AI

make sure to introduce the term "bot"

II. Real-Time Strategy Games

Real-time Strategy (RTS) is a sub-genre of strategy games where players need to build an economy (gathering resources and building a base) and military power (training units and researching technologies) in order to defeat their opponents (destroying their army and base). From a theoretical point of view, the main differences between RTS games and traditional board games such as Chess are:

- They are *simultaneous move* games, where more than one player can issue actions at the same time. Additionally, these actions are *durative*, i.e. actions are not instantaneous, but take some amount of time time to complete.
- RTS games are "real-time", which actually means is that each player has a very small amount of time to decide the next move. Compared to Chess, where players have several minutes to decide the next action, in Starcraft, the game executes at 24 iterations per second, which means that players only have 55ms to decide a move, before the game state changes.
- Most RTS games are partially observable: players can only see the part of the map that has been explored.
- Most RTS games are non-deterministic.
- And finally, the complexity of these games, both in terms of state space size and in terms of number of actions available at each decision cycle is very large. For example, the state space of Chess is typically estimated to be around 10^{50}, heads up no-limit texas holdem poker around 10^{80}, and Go around 10^{170}. In comparison, the state space of Starcraft in a typical map is estimated to be at least 10^{10000}.

For those reasons, standard techniques used for playing classic board games, such as alpha-beta search, cannot be directly applied to solve RTS games without the definition of some level of abstraction, or some other simplification. Interestingly enough, humans seem to be able to deal with the complexity of RTS games, and are still vastly superior to computers in these type of games [2]. For those reasons, a large spectrum of techniques have been attempted to deal with this domain, as we will describe below. The remainder of this section is devoted to describe Starcraft as a research testbed, and on detailing the open challenges in RTS game AI.

A. StarCraft

Starcraft: Brood War is an immensely popular RTS game released in 1998 by Blizzard Entertainment. Starcraft is set in a science-fiction based world where the player must choose one of the three races: Terran, Protoss or Zerg. One of the most remarkable aspects of Starcraft is that the three races in Starcraft are extremely well balanced:

- Terrans, provide units that are versatile and flexible giving a balanced option between Protoss and Zergs.
- Protoss units have lengthy and expensive manufacturing process, but they are strong and resistant. These conditions makes players follow a strategy of quality over quantity.
- Zergs, the insectoid race, units are cheap and weak. They can be produced fast, encouraging players to overwhelm their opponents with sheer numbers.

Figure 1 shows a screenshot of Starcraft showing a player playing Terrans. In order to win a Starcraft game, players must first gather resources (minerals and gas), which they can spend in creating additional buildings and units. As resources become available, players need to allocate them for creating more buildings (which reinforce the economy, and allow players to

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Fig. 1. A screenshot of Starcraft is this a good screenshot? can we actually have a screenshot? or is this copyrighted? Do we even want a screenshot?.

create units or unlock stronger units) and train attack units. Units must be distributed to accomplish different tasks such as reconnaissance, defense and attack. While performing all of those tasks, players also need to strategically understand the geometry of the map at hand, in order to decide where to place new buildings (concentrate in a single area, or expand to different areas) or where to set defensive outposts. Finally, when offensive units of two players meet, each player must quickly maneuver each of the units in order to fight a battle, which requires quick and reactive control of each of the units in order to successfully fight the battle.

A typical Starcraft map is defined as a rectangular grid, typically ranging between 64x64 to 128x128 in size (although the resolution at which units move is finer), and each player can control up to 200 units (not including buildings). Moreover, each different race contains between 30 to 35 different types of units and buildings, each one with a significant number of special abilities. All these factors together make Starcraft a significant challenge, in which humans are still much better than computers. Indeed, best Starcraft AIs are ranked between D and D^- on the iCCup[1] ranking system, where average amateur players are ranked between C^+ and B. For comparison, Starcraft professional players are usually ranked between A^- and A^+.

B. Challenges in RTS Game AI

Early research in AI for RTS games [1] identified the following sic challenges:

- Resource management
- Decision making under uncertainty
- Spatial and temporal reasoning
- Collaboration (between multiple AIs)
- Opponent modeling and learning
- Adversarial real-time planning

While there has been a significant work in many, others have been untouched (e.g. collaboration). Moreover, recent research in this area has identified several additional research challenges, such as how to exploit the massive amounts of existing domain knowledge (strategies, build-orders, replays, and so on). Below, we describe current challenges in RTS Game AI, grouped in six main different areas.

1) Planning: As mentioned above, the size of the state space in RTS games is vastly larger than that of traditional board-games such as Chess or Go. Additionally, the number of actions that can be executed at given instant of time is also much larger. Thus, standard adversarial planning approaches, such as game tree search are not directly applicable. As we elaborate later, planning in RTS games can be seen as having multiple levels of abstraction: at a higher level, players need long-term planning capabilities, in order to develop a strong economy in the game; at a low level, individual units need to be moved in coordination to fight battles taking into account the terrain and the opponent. Techniques that can address this large planning problems by either sampling, or hierarchical decomposition do not yet exist.

2) Learning: Given the difficulties in playing RTS games by directly using adversarial planning techniques, many research groups have turned attention to learning techniques. We can distinguish three types of learning problems in RTS games:

- *Prior learning*: how can we exploit available data, such as existing replays, or information about specific maps for learning appropriate strategies before hand? A significant amount of work has gone in this direction.
- *In-game learning*: how can bots can deploy online learning techniques that allow them to improve their game play while playing a game? these techniques might include reinforcement learning techniques, but also opponent modeling. The main problem again is the fact that the state space is too large.
- *Inter-game learning*: what can be learned from one game that can be used to increase the chances of victory in the next game? Some work has used simple game-theoretical solutions to select amongst a pool of predefined strategies, but the general problem remains unanswered.

3) Uncertainty: Adversarial planning under uncertainty in domains of the size of RTS games is still an unsolved challenge. In RTS games, there are two main kinds of uncertainty. First, the game is partially observable, and players cannot observe the whole game map (like in Chess), but need to scout in order to see what the opponent is doing. This type of uncertainty can be lowered by good scouting, and knowledge representation (to infer what is possible given what has been seen). Second, there is also uncertainty arising from the fact that the games are adversarial, and a player cannot predict the actions that the opponent(s) will execute. For this type of uncertainty, the AI, as the human player, can only build a sensible model of what the opponent is likely to do.

4) Spatial and Temporal Reasoning: Spatial reasoning is related to each aspect of the terrain exploitation. Spatial reasoning is involved in tasks such as building placing, or base expansion. In the former, the player needs to carefully consider buildings position into its own bases to both protect them by creating a wall against invasions and to avoid bad configurations where large units could be stuck. In base expansion, the player has to choose good available emplacements to build a new base, regarding its own position and opponent's bases.

[1] http://www.iccup.com/starcraft/

Finally, spatial reasoning is key to tactical reasoning: players need to decide where to place units for battle, favoring, for instance, engagements when the opponent's units are into a bottleneck.

Analogously, temporal reasoning is key in tactical or strategic reasoning. For example, timing attacks and retreats to gain advantage. At a higher strategic level, players need to reason about when to perform long-impact economic actions such as upgrades, building construction, strategy switching, etc. all taking into account that the effects of these actions are not immediate, but longer term.

5) Domain Knowledge Exploitation: In traditional board-games such as Chess, researchers have exploited the large amounts of existing domain knowledge to create good evaluation functions to be used by alpha-beta search algorithms, extensive opening books, or end-game tables. In the case of RTS games, it is still unclear the ways in which the significantly large amount of domain knowledge (in the forms or strategy guides, replays, etc.) can be exploited by bots. Most work in this area has focused on two main directions: on the one hand, researchers are finding ways in which to hard-code existing strategies into bots, so that bots only need to decide which strategies to deploy, instead of having to solve the complete problem of deciding which actions to execute by each individual unit at each time step. One the other hand, large datasets of replays have been created [3], from where strategies, trends or plans have been tried to learn. However, Starcraft games are quite complex, and how to automatically learn from such datasets is still an open problem.

6) Task Decomposition: For all the previous reasons, most existing approaches to play games like Starcraft work by decomposing the problem of playing a RTS game into a collection of smaller problems, to be solved independently. Specifically, a common subdivision is:

- *Strategy*: often called *macro-management*, corresponds to the high-level decision making process. This is the highest level of abstraction for the game comprehension. RTS games are all about finding an efficient strategy or counter-strategy against a given opponent. It concerns the whole set of units and buildings one owns.
- *Tactics*: are the implementation of the current strategy. It implies army and building positioning, movements, timing, and so on. Tactics concerns a group of units.
- *Reactive control*: often called, *micro-management* is the implementation of tactics. This consists in moving, targeting, firing, fleeing, hit-and-run techniques (aka "kiting") during battle. Reactive control focuses on a specific unit.
- *Terrain analysis*: consists in the analysis of regions composing the map: choke-points, minerals and gas emplacements, low and high walkable grounds, islands, etc.
- *Intelligence gathering*: corresponds to information collected about the opponent. Because of the fog-of-war, players must regularly send scouts to localize and spy enemy bases.

The reader can find a good presentation of task decomposition for AIs playing RTS in [4]. Although the previous task decomposition is common, a significant challenge is on designing architectures so that the individual AI techniques

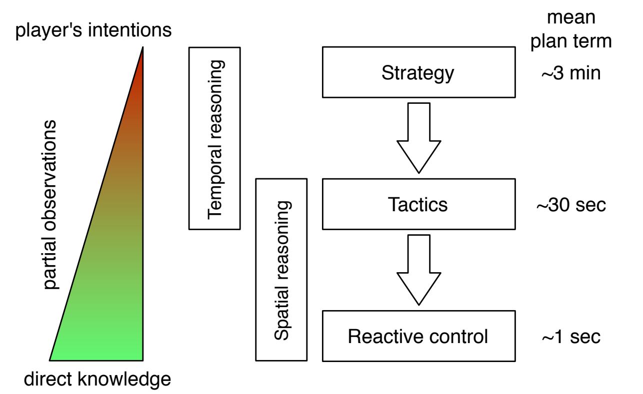

Fig. 2. RTS AI levels of abstraction and their properties: uncertainty (from intentions and from partial observation) is going higher as the abstraction levels are raising. The timings on the right correspond to an estimate of the duration of a behavior switch in StarCraft. Spatial and temporal reasoning are indicated for part for which greedy solutions are really not efficient.

that address each of those tasks can communicate and effectively work together, resolving conflicts, prioritizing resources between them, etc.

III. Existing work on RTS Game AI

Systems that play RTS games need to address most, if not all, the aforementioned problems together. Therefore, it is hard to classify existing work on RTS AI as addressing the different problems above. For that reason, in order to classify existing work on RTS AI, we will divide the existing work according to three levels of abstraction (division that is widely used by RTS players): strategy, tactics and reactive control (micro-management).

Figure 2 graphically illustrates how strategy, tactics and reactive control are three points in a continuum scale where strategy corresponds to decisions making processes that affect long spans of time (several minutes in the case of Starcraft), reactive control corresponds to low-level second-by-second decisions, and tactics sit in the middle. Also, strategic decisions reason about the whole game at once, whereas tactical or reactive control decisions are localized, and affect only specific groups of units. Typically, strategic decisions constraint future tactical decisions, which in turn condition reactive control. Moreover, information gathered while performing reactive control, can cause reconsideration of the tactics being employed; which could trigger further strategical reasoning.

Following this idea, we consider strategy to be everything related to the technology trees, build-order[2], upgrades, and army composition. It is the most deliberative level, as a player selected and performs a strategy with future stances (aggressive, defensive, economy, technology) and tactics in mind. We consider tactics, everything related to confrontations between groups of units. Tactical reasoning involves both spatial (exploiting the terrain) and temporal (army movements) reasoning, constrained on the possible types of attacks by the army composition of the player and their opponent. Finally, we

[2]The *build-order* is the specific sequence in which buildings of different types will be constructed at the beginning of a game, and completely determines the long-term strategy of a player.

will call reactive control (also known as micro-management) to how the player controls individual units to maximize their efficiency (when executing tactics) in real-time and adversary conditions. The main difference between tactics and reactive control is that tactical reasoning typically involves some sort of planning ahead for some short spans of time, whereas reactive control involves no planning ahead whatsoever.

For example, after starting a game, a player might decide to use a *rushing* strategy (which involves quickly building an army and sending it to attack as early as possible in the game); then, when performing the attack use a *surrounding* tactic, where the player tries to surround the enemy cutting potential escape routes; finally, while executing the surrounding tactic, the player might decide to use reactive control techniques that command individual units to perform repeated *attack and flee* movements, to maximize the efficiency of each of the units being used in the attack.

A. Strategy

Strategic decision making in real-time domains is still an open problem. In the context of RTS games is has been addressed using many AI techniques, like hard-coded approaches, planning-based approaches, or machine learning-based approaches. Let us cover each of these approaches in turn.

Hard-coded approaches have been extensively used in commercial RTS games. The most common approaches use finite state machines (FSM) [5] in order to let the AI author hard-code the strategy that the AI will employ. The idea behind FSMs is to decompose the AI behavior into easily manageable states, such as "attacking", "gathering resources" or "repairing" and establish the conditions that trigger transitions between them. Commercial approaches also include Hierarchical FSMs, in which FSMs are composed hierarchically. These hard-coded approaches have achieved a significant amount of success, and, as we will discuss later, have also been used in many academic RTS AI research systems, as discussed in Section IV. However, strategic decision making is a hard problem, and these hard-coded approaches struggle to encode dynamic, adaptive behaviors.

Approaches using planning techniques have also been explored in the literature. For example Ontañón et al. [6] explored the use of real-time case-based planning (CBP) in the domain of Wargus (a Warcraft II clone). In their work, they used human demonstration to learn plans, that are then composed at run-time in order to form full-fledges strategies to play the game. In [7] they improve over their previous CBP approach by using situation assessment for improving the quality and speed of plan retrieval. Hierarchical Task-Network (HTN) planning has also been explored with some success in the context of simpler first-person shooter games. Planning approaches offer more adaptivity of the AI strategy compared to hard-coded approaches. However, the real-time constraints of RTS games limit the planning approaches that can be applied, being HTN and case-based planning the only ones explored so far. Moreover, none of these approaches addresses any timing or scheduling issues, which are key in RTS games. On notable exception is the work of Churchill and Buro [8], who used planning in order to construct its economic build-orders taking into account timing constraints of the different actions.

Concerning machine learning-based approaches, Weber and Mateas [9] proposed "a data mining approach to strategy prediction" and performed supervised learning (from buildings features) on labeled StarCraft replays. Dereszynski et al. [10] used HMM to learn the transition probabilities of sequences of constructions and kept the most probables to produce probabilistic behavior models (in StarCraft). Synnaeve and Bessière [11] used the dataset of [9] and presented a Bayesian semi-supervised model to learn from replays and predict openings (early game strategies) from StarCraft replays. The openings are labeled by EM clustering considering appropriate features. Then, in [12], they presented an unsupervised learning Bayesian model for tech-tree prediction, still using replays. Finally, evolutionary approaches to determine priorities of high level tasks was explored by Young and Hawes in their QUORUM system [13], showing improvement over static priorities.

Also falling into the machine-learning category, a significant group of researchers has explored case-based reasoning (CBR) [14] approaches for strategic decision making. For example Aha et al. [15] used CBR to perform dynamic plan retrieval in the Wargus domain. Hsieh and Sun [16] based their work on [15] CBR model and used StarCraft replays to construct states and building sequences ("build orders"). Finally, Schadd et al. [17] applied a CBR approach to opponent modeling through hierarchically structured models of the opponent behavior and they applied their work to the Spring RTS (Total Annihilation clone).

One final consideration is that RTS games are typically partially observable. For example games like StarCraft implement the "fog of war" idea, which basically means that a player can only see the areas of the map close to her own units. Areas of the map away from the field of view of individual units are not observable. Therefore, in order to play an RTS game, players need to scout the opponent in order to obtain information about the opponent's strategy. Very few of the previous approaches deal with this problem, and use perfect information all the time (in the case of commercial games, most AI implementations cheat, since they have perfect information). In commercial games, in order to make the human player believe the built-in AI of this games does scouting, sometimes they simulate some scouting tasks as Bob Fitch described in his AIIDE 2011 keynote for the WarCraft game series and StarCraft: Broodwar. A notable exception is the work of Weber et al. [18], who used a particle model with a linear trajectory update to track opponent units under fog of war in StarCraft. They also produced tactical goals through reactive planning and goal-driven autonomy [19], [20], finding the more relevant goal(s) to spawn in unforeseen situations.

B. Tactics

Tactical reasoning involves reasoning about the different abilities of the units in a group of units and about the environment (terrain) and positions of the different units in order to gain military advantage in battles. For example, it would be a very bad tactical decision to place fast, invisible or flying units (typically expensive) in the first line of fire against slower heavier units, since they will be wiped out fast. We will divide the work on tactical reasoning in two parts: terrain analysis and decision making.

Terrain analysis supplies the AI with structured information about the map in order to help making decisions. This analysis is usually performed off-line, in order to save CPU time during the game. For example, Pottinger [21] described the *BANG* engine implemented by Ensemble Studios for the game Age of Empires II. This engine provides terrain analysis functionalities to the game using influence maps and areas with connectivity information. Forbus et al. [22] showed the importance to have qualitative spatial information for wargames, for which they used geometric and pathfinding analysis. Hale et al. [23] presented a 2D geometric navigation mesh generation method from expanding convex regions from seeds. Finally, Perkins [24] applied Voronoi decomposition (then pruning) to detect regions and relevant choke points in RTS maps. This approach is implemented for StarCraft in BWTA[3].

Concerning tactical decision making, many different approaches have been explored such as machine learning or game tree search. Concerning machine learning approaches, Hladky and Bulitko [25] benchmarked hidden semi-Markov models (HSMM) and particle filters in first person shooter games (FPS) units tracking. They showed that the accuracy of occupancy maps was improved using movement models (learned from the player behavior) in HSMM. Kabanza et al. [26] improve the probabilistic hostile agent task tracker (PHATT [27], a simulated HMM for plan recognition) by encoding strategies as HTN, used for plan and intent recognition to find tactical opportunities. Sharma et al. [28] combined CBR and reinforcement learning to enable reuse of tactical plan components. Cadena and Garrido [29] used fuzzy CBR (fuzzy case matching) for strategic and tactical planning. Finally, [30] combined space abstraction into regions from [24] and tactical-decision making by assigning scores (economical, defenses, etc.) to regions and looking for their correspondences to tactical moves (attacks) in pro-gamers replays.

Game tree search techniques have also been explored for tactical decision making. [31] applied Monte-Carlo planning to a capture-the-flag mod of Open RTS. Balla and Fern [32] applied the UCT algorithm (a Monte Carlo Tree Search algorithm) to tactical assault planning in Wargus.

Additionally, scouting is equally important in tactical decision making as in strategic decision making. However, as mentioned earlier, very little work has been done in this respect, being that of Weber et al. [18] the only exception.

C. Reactive Control

Reactive control, also called micro-management in RTS games, aims at maximizing the effectiveness of units, including simultaneous control of units of different types in complex battles on heterogeneous terrain.

[3]http://code.google.com/p/bwta/

Potential fields (or influence maps) have been found to be a useful technique for reactive decision making. Some uses of potential fields in RTS games are: avoiding obstacles (navigation), avoiding opponent fire [33], or staying at maximum shooting distance [34]. Potential fields have also been combined with A* path-finding to avoid local traps [35]. Hagelbäck and Johansson [36] presented a multi-agent potential fields based bot able to deal with fog of war in the Tankbattle game. Avery et al. [37] and Smith et al. [38] co-evolved influence map trees for spatial reasoning in RTS games. Danielsiek et al. [39] used influence maps to achieve intelligent squad movement to flank the opponent in a RTS game. A drawback for potential field-based techniques is the large number of parameters that has to be tuned in order to achieve the desired behavior. Approaches for automatically learning such parameters have been explored, for example, using reinforcement Learning [40], or self-organizing-maps (SOM) [41]. We would like to note that potential fields are a reactive control technique, and as such, they do not perform any form of lookahead. As a consequence, these techniques are prone to make units stuck in local optima.

There has been a significant amount of work on using machine learning techniques for the problem of reactive control. Bayesian modeling has been applied to inverse fusion of the sensory inputs of the units [42], which subsumes potential fields, allowing for integration of tactical goals directly in micro-management.

Additionally, there has been some interesting uses of reinforcement learning (RL) [43]: Wender and Watson [44] evaluated the different major RL algorithms for (decentralized) micro-management, which perform all equally. Marthi et al. [45] employ concurrent hierarchical Q-learning (units Q-functions are combined at the group level) RL to efficiently control units in a “one robot with multiple effectors” fashion. Madeira et al. [46] advocate the use of prior domain knowledge to allow faster RL learning and applied their work on a turn-based strategy game. The actions spaces to explore is gigantic for real game setups. It requires to use the structure of the game in a partial program (or a partial Markov decision process) and a shape function (or a heuristic) [45]. Another approach is that proposed by Jaide and Muñoz-Avila [47] through learning just one Q-function for each unit type, in order to cut down the search space.

Other approaches that aim at learning the parameters of an underlying model have also been explored. For example Ponsen and Spronck [48] used evolutionary learning techniques, but face the same problem of dimensionality. The difficulty to work with multi-scale goals and plans is handled directly by case-based reasoning (CBR), which has been adapted for units behavior with continuous action models [49], an integrated RL/CBR algorithm using continuous models, or with hybrid CBR/RL transfer learning [28]. Reactive planning [19], a decompositional planning similar to hierarchical task networks [50], allows for plans to be changed at different granularity levels and so for multi-scale (hierarchical) goals integration of low-level control. Synnaeve and Bessière [42] achieve hierarchical goals (coming from tactical decisions) integration through the addition of another sensory input corresponding to the goal's objective. Finally, evolutionary optimization by simulating fights can easily adapted to any parameter-dependent micro-management control model, as shown by [51] which optimizes an AIIDE 2010 micro-management competition bot.

Other research falling into reactive control has been performed in the field of cognitive science, where Wintermute et al. [52] have explored human-like attention models (with units grouping and vision of a unique screen location) for micro-management.

Finally, although pathfinding does not fall under our previous definition of reactive control, we include it in this section, since it is typically performed as a low-level service, not part of either tactical nor strategical reasoning (although there are some exceptions, like the tactical pathfinding of Danielsiek et al. [39]). The most common pathfinding algorithm is A*, but its big problem is CPU time and memory consumption, hard to satisfy in a complex, dynamic, real-time environment with large numbers of units. Even if specialized algorithms, such as D*-Lite [53] exist, it is most common to use A* combined with a map simplification technique that generates a simpler navigation graph to be used for pathfinding. An example of such technique is Triangulation Reduction A*, that computes polygonal triangulations on a grid-based map [54]. Considering movement for groups of units, rather then individual units, techniques such as steering of flocking behaviors [55] can be used on top of a path-finding algorithm in order to make whole groups of units follow a given path. In recent commercial RTS games like Starcraft 2 or Supreme Commander 2, flocking-like behaviors are inspired of continuum crowds ("flow field") [56]. A comprehensive review about (grid-based) pathfinding was recently done by Sturtevant [57].

D. Holistic Approaches

[Santi: some RTS AI techniques attempt to address the problem in a holistic way, for example the Darmok system, is there enough work on this for justifying a whole subsection? or should we just spread the few pieces of work on this over the previous sections].

IV. State of the Art Bots for Starcraft

Thanks to the recent organization of international game AI competitions focused around the popular StarCraft game (see Section V), several groups have been working on integrating many of the techniques described in the previous section into complete "bots", capable of playing complete StarCraft games. In this section we will overview some of the currently available top bots, and focus, first on the architecture being used to integrate all the techniques being used for the different aspects of the bot, and then on which subsets of techniques are used for each bot.

A. RTS Bot Architectures

Playing an RTS game involves dealing with all the problems described above. A few approaches, like CAT [15], Darmok [58] or ALisp [45] try to deal with the problem in a monolithic manner, by using a single AI technique. This resembles approaches to solve other games, such as Chess or Go, where a single game-tree search approach is enough to play the game at human level. However, none of those systems aims at achieving near human performance. In order to achieve human-level performance, RTS AI designers use a lot of domain knowledge in order to divide the task of playing the game into a collection of sub-problems, which can be dealt-with using individual AI techniques (as discussed in the previous section).

Figure 3 shows some representative examples of the integration architectures used by different bots in the AIIDE and CIG Starcraft AI competitions (see Section V): BroodwarQ [?], Nova [?], UAlbertaBot [?], Skynet [?], SPAR [?], AIUR [?], and BTHAI [?]. Each box represents an individual module with a clearly defined task (only modules with a black background can send actions directly to Starcraft). Dashed arrows represent data flow, and solid arrows represent control (when a module can command another module to perform some task). For example, we can see how SPAR is divided in two sets of modules: *situation analysis* and *decision making*, the first with three modules dedicated to analyze the current situation of the game, and the later with 4 modules dedicated to exploit that information to decide what to do. We can see how the decision making aspect of SPAR is organized hierarchically, with the higher-level module (*strategic decision*) issuing commands to the next module (*tactical decision*), which sends commands to the next module (*action implementation*), and so on. Only the lower-level modules can send actions directly to Starcraft.

On the other hand, bots such as NOVA or BroodwarBotQ (BBQ) only use a hierarchical organization for *micro-management* (controlling the attack units), but use a decentralized organization for the rest of the bot. In Nova and BBQ, there is a collection of modules that control different aspects of the game (workers, production, construction, etc.). These modules can all send actions directly to Starcraft. In Nova those modules coordinate mostly through writing data in a shared blackboard, and in BBQ they coordinate only when they have to use a shared resource (unit) by means of an arbitrator.

By analyzing the structure of these bots, we can see that there are two main tools that can be used when designing an integration architecture:

- *Abstraction*: complex tasks can be formulated at different levels of abstraction. For example, playing an RTS game can be seen as issuing individual low-level actions to each of the units in the game, or at a higher level, it can be seen as deploying a specific strategy (e.g. a "BBS strategy", or a "Reaver Drop" strategy). Some bots, reason at multiple levels of abstraction at the same time, making the task of playing Starcraft simpler. Assuming that each module in the architecture of a bot has a goal and determines some actions to achieve that goal, the actions determined by higher-level modules are considered as the goals of the lower level modules. In this way, each module can focus on reasoning at only one level of abstraction, thus, making the problem easier.
- *Divide-and-conquer*: playing a complex RTS, such as Starcraft, requires performing many conceptually differ-

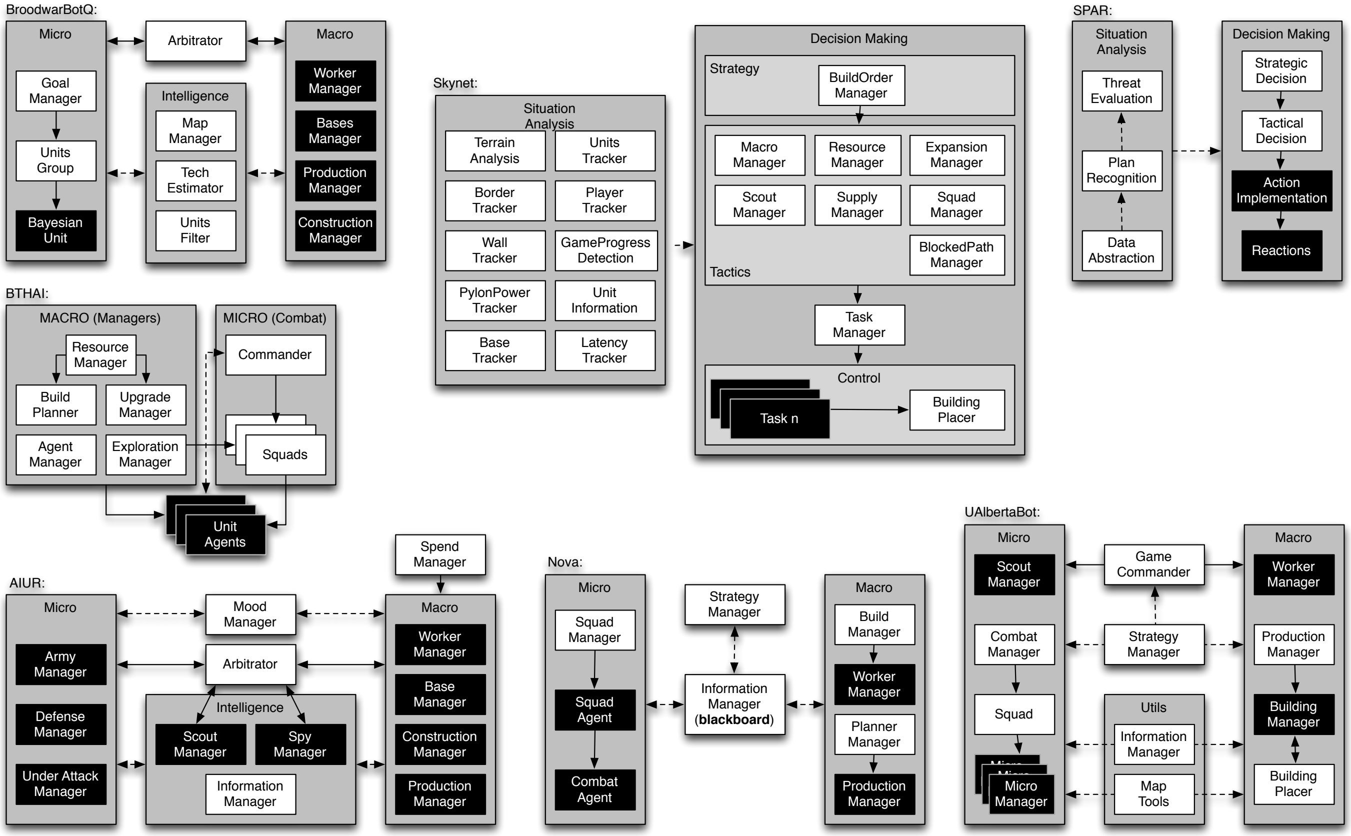

Fig. 3. Architecture of 6 Starcraft bots obtained by analyzing their source code. Modules with black background sent commands directly to Starcraft, dashed arrows represent data flow, and solid arrows represent control.

ent tasks, such as gathering resources, attacking, placing buildings, etc. Assuming each of these tasks can be performed relatively independently and without interference, we can have one module focusing on each of the tasks independently, thus making the problem easier.

If we imagine the different tasks to perform in a complex RTS game in a two-dimensional plane, where the vertical axis represents abstraction, and the horizontal axis represents the different aspects of the game (micro-management, resource gathering, etc.), abstraction can be seen as dividing the space with horizontal lines, whereas divide-and-conquer divides the space using vertical lines.

Different bots, use different combinations of these two tools. Looking back at Figure 3, we can see the following use of abstraction and divide-in-conquer in the bots:

- BroodwarBotQ[4]: uses abstraction for micro-management, and divide-and-conquer for macro-management and intelligence gathering. To avoid conflicts between modules (since the individual tasks of each of the modules are not completely independent), BBQ uses an arbitrator.
- Nova[5]: is similar in design as BroodwarBotQ, and uses abstraction for micro-management, and divide-and-conquer for macro-management. The differences are that Nova does not have an arbitrator to resolve conflicts, but has a higher-level module (*strategy manager*), which posts information to the blackboard that the rest of modules follow (thus, making use of abstraction).
- UAlbertaBot[6]: also uses abstraction in micro-management like the previous two bots. But it also uses it in macro-management: as can be seen, the production manager sends commands to the building manager, who is in charge of producing the buildings. This bot also uses divide-and-conquer, and tasks like scouting and resource gathering are managed by separate, independent modules.
- Skynet[7]: makes extensive use of both abstraction and divide-and-conquer. Considering the decision making component of Skynet, we can see a high level module that issues commands to a series of tactics modules. The collection of tactic modules queue *tasks* (that are analogous to the abstract actions used in SPAR). Each different task has a specific low level module that knows how to execute it. Thus, Skynet uses a 3 layered abstraction hierarchy, and uses divide-and-conquer in all levels except the highest.
- SPAR[8]: only uses abstraction. Its high-level module determines the strategy to use, and the tactical decision module divides it into a collection of *abstract actions*, that are

[4]http://github.com/SnippyHolloW/BroodwarBotQ
[5]http://nova.wolfwork.com/
[6]http://code.google.com/p/ualbertabot/
[7]http://code.google.com/p/skynetbot/
[8]http://www.planiart.usherbrooke.ca/projects/spar/

executed by the lower-level modules.

- AIUR[9]: is mainly divide-and-conquer oriented, for macro as well as for micro, with a slight abstraction on macro due to a SpendManager deciding how to spend and share resources among Base, Production and Construction Managers. At the beginning of a game, the MoodManager initializes a "mood" which will influence both tactics and strategy. Tactics are divided into three independent managers: the *Defense Manager*, controlling military units when there is nothing special, the *Under Attack Manager*, activated when the opponent is attacking our bases, and the *Army Manager*, taking control of units when it is time to attack, following a timing given by the current mood. This bot does not manage however any kind of reactive controls so far.
- BTHAI[10]: uses a two-tier abstraction hierarchy, where a collection of high-level modules command a collection of lower-level agents in charge of each of the units. At the high-level, BTHAI uses divide-and-conquer, having multiple high-level modules issuing commands to the lower-level units.

Additionally, except for BTHAI, all other agents use divide-and-conquer at a higher-level bot design and divide all the modules into two or three categories: *information gathering* and *decision*, or *information gathering*, *micro-management* and *macro-management*.

Some bots using divide-and-conquer, assume that each of the modules can act independently and that their actions can be executed without interference. BBQ, UAlbertaBot and AIUR, however use an arbitrator (*Game Commander'* in UAlbertaBot) that makes sure that modules do not send contradictory orders to the same unit. However, very little bots handle the problem of how to coordinate resource usage amongst modules, for instance BTHAI uses a first-come-first-serve policy for spending resources, the first module that requests resources is the one that gets them. Nova and Skynet are exceptions, and implement some rudimentary prioritization based on the high level strategy. Following available resources and timing, AIUR's *Spend Manager* orders Base, Production and Construction Managers what they have to build/produce. It also orders to start tech research and upgrades. The idea here is not to allocation resources among different managers to satisfy a need (informally: "I want to do that, so I need M minerals and G gas"), but to do the opposite, that is, to find how the AI can spend the available money: "I have right now M minerals and G gas, so how can I spend it?".

One interesting aspect of the seven bots described above is that, while all of them - except AIUR - are reactive at the lower level (reactive control), most if not all of them, are scripted at the highest level of abstraction. BTHAI reads build and squad formations from a predefined script, Nova's *Strategy Manager* is a predefined finite-state machine, BBQ's construction manager reads the build order from a predefined script, and Skynet's *BuildOrder Manager* is basically a predefined script. Such scripts describe the strategy that the bots will use, however, such strategy is always fixed. One could see this pre-scripting as if each bot defined a "high-level programming language" to describe Starcraft strategies, and the bots themselves are just interpreters of such strategy. Compared to current approaches for Chess or Go, this scripting seems a rigid and inflexible, but responds to the much higher complexity of the Starcraft game. An interesting exception to that is UAlbertaBot, which uses a search algorithm in the *Production Manager* to find near-optimal build orders. Another interesting case is AIUR, that uses a *Mood Manager* to randomly pick a mood among six (cheese, rush, aggressive, defensive, macro, fast expand), which will influence the build order, strategy and tactics. All of them scripted so far, but build orders can been modified but the Spend Manager, following available resources. This mood can change during the game, regarding the opponent behavior.

In conclusion, we can see that there are two basic tools that can be used in an integration architecture: abstraction and divide-and-conquer, which are widely used by the existing Starcraft bots. For space reasons, we do not include an exhaustive comparison of the architectures of all the participating bots. Some other bots have been documented by their authors, such as SCAIL [59] or QUORUM [13].

This section has focused on discussing the architecture of existing Starcraft bots. Let us now focus on what is the state of the art on the techniques used for each of the individual modules used by them.

B. Individual AI Techniques

TODO

V. Recent Starcraft AI Competitions

In order to inject new AI code into the StarCraft game, all recent tournaments attached to scientific conferences employ the Brood War Application Programming Interface (BWAPI)[11] which enables replacing the human player interface with a C++ library, some auxiliary libraries and the bot code. A consequence of this indirect way of integrating new bots is that every machine can only run one custom bot, requiring two computers for a 2-player game.

The following subsections summarize the results of all the Starcraft AI competitions held at the AIIDE (Artificial Intelligence for Interactive Digital Entertainment) and CIG (Computational Intelligence in Games) conferences during the past years.

A. AIIDE

Started in 2010, the AIIDE StarCraft AI Competition[12] is the most well known and longest running StarCraft AI Competition in the world. Each year AI bots are submitted by competitors to do battle within the retail version of StarCraft: BroodWar, with prizes supplied by Blizzard Entertainment. This competition has been made possible by the BWAPI StarCraft programming interface, which allows players to

[9] http://code.google.com/p/aiurproject/
[10] http://code.google.com/p/bthai/
[11] http://code.google.com/p/bwapi/
[12] http://www.StarCraftAICompetition.com

write programs which can retrieve game data and issue game commands to StarCraft via an easy to use C++ API.

The first competition in 2010 was organized and run by Ben Weber in the Expressive Intelligence Studio at University of California , Santa Cruz[13]. 26 total submissions were received from around the world. As this was the first year of the competition, and little infrastructure had been created, each game of the tournament was run manually on two laptop computers and monitored by Ben to record the results. Also, no persistent data was kept for bots to learn about opponents between matches.

The 2010 competition had 4 different tournament categories in which to compete. Tournament 1 was a flat-terrain unit micromanagement battle consisting of four separate unit composition games. Of the six competitors, FreSCBot won the competition with Sherbrooke coming in 2nd place. Tournament 2 was another micro-focused game with non-trivial terrain. Two competitors submitted for this category, with FreSCBot once again coming in 1st by beating Sherbrooke.

Tournament 3 was a tech-limited StarCraft game on a single known map with no fog of war enforced. Players were only allowed to choose the Protoss race, with no late game units allowed. 8 bots faced off in this double-elimination tournament with mimicbot taking first place over botnik in the final. As this was a perfect information variant of StarCraft, mimicbot adopted a strategy of ”mimics its opponent’s build order, gaining an economic advantage whenever possible” which worked quite well.

Tournament 4 was the complete game of *StarCraft: BroodWar* with fog of war enforced. The tournament was run with a random pairing double-elimination format with each match being best of 5 games. Competitors could play as any of the three races, with the only limitations in gameplay being those which were considered ’cheating’ in the StarCraft community. A map pool of 5 well-known professional maps was announced to competitors in advance, with a random map being chosen for each game.

Results are shown in Table I. The team that won was Overmind[14], from University of California, Berkeley. Using the Zerg race, their strategy was to defend early aggression with zergling units while amassing mutalisk units which they used to contain and eventually defeat their opponents. The mutalisk is a very fast and agile flying unit which is able to attack while moving with no drawback, which makes them quite a powerful unit when controlled by a computer, which has super-human input speeds. Overmind used a potential-field based micromanagement system to guide their mutalisks, which led them to victory. Krasi0 came in 2nd place with a standard defensive Terran opening strategy which transitioned into mech play in the late game.

In 2011 the competition was hosted by the University of Alberta, with organization by Michael Buro and David Churchill[15]. Due to a lack of entrants in tournament categories 1-3 in the 2010 competition, it was decided that only the full game category would be played in the 2011 competition. Another important change in the 2011 competition was the introduction of automated tournament-managing software running StarCraft games simultaneously on 20 computers, allowing a total of 1170 games to be played in the far less time than the 108 games of the 2010 competition. This increase in games played also allowed the tournament to switch to a round-robin format, eliminating the “luck” factor of the pairings inherent in bracket style tournaments. The bot which achieved the highest win percentage over the course of the competition would be determined the winner. Also decided was that the competition would become open-source, in an effort not only to prevent possible cheating, but to promote healthy competition in future tournaments by giving newcomers and easier entry point by basing their design off of previous bots.

TABLE I
RESULTS OF THE AIIDE 2010 COMPETITION.

Position	bot
1	Overmind
2	Krasi0
3	Chronos

In the end, Skynet won the competition with its solid Protoss play (results are summarized in Table II). The bot executed one of a small set of strategies randomly at the start of the match based on the map and the race of the opponent. Skynet would then amass a medium to large sized army and expand before moving out to attack. Good use of Dragoon range and kiting micromanagement allowed it to hold off the early aggression of other bots such as UAlbertaBot, which came in 2nd.

UAlbertaBot used an early zealot-rush strategy to take advantage of the power of early game Protoss units. It would send out the first zealots which were made and immediately attack the enemy base, using a unit counting heuristic to determine whether or retreat or keep pushing. Of note is that UAlbertaBot used an online planning algorithm to construct all of its economic build-orders [8], as no hard-coded build orders were used.

AIUR also chose Protoss, with a strategy which was in between Skynet and UAlbertaBot in terms of attack timings. At that time, AIUR chose one mood among five (leading to slightly different strategies and tactics) at the beginning of a game and kept it until the end. These five moods were:

- Rush: where the bot tries early attacks, and have good probabilities to send the two or three first Zealots to harass the opponent.
- Aggressive: where we have less chance to perform harasses with the first Zealots, and the first attack is usually a bit delayed with regard to the Rush mood.
- Macro: where the AI do not try any early attacks and focus a bit more on its economy before attacking.
- Defense: where the AI “turtles” and wait to have a consequent army before running an attack.
- Fast expand: where the first building constructed it a base expansion, for a very economical-oriented game.

Notice that build orders are not fully hard-coded since they

[13]http://eis.ucsc.edu/StarCraftAICompetition
[14]http://overmind.cs.berkeley.edu
[15]https://skatgame.net/mburo/sc2011/

TABLE II
RESULTS OF THE AIIDE 2011 COMPETITION.

Position	bot	win %
1	Skynet	88.9%
2	UAlbertaBot	79.4%
3	AIUR	70.3%
4	ItayUndermind	65.8%
5	EISBot	60.6%

can be altered by AIUR's Spend Manager.

Of note in these results was that a rock-paper-scissors effect happened among the top 3 finishers. Of the 30 rounds, Skynet beat UAlbertaBot 26 times, UAlbertaBot beat AIUR 29 times, and AIUR beat Skynet 19 times. Another notable result is that Overmind did not choose to compete despite winning the 2010 competition. After the competition, many bot programmers (including the Overmind team) realized that their 2010 strategy was quite easily defeated by early game rushing strategies, and so they submitted a Terran bot instead, called Undermind, which finished in 7th.

After the competition was over, a man vs. machine match was held between the winner (Skynet) and an ex-professional StarCraft player named Oriol Vinyals. Oriol was a competitor in the 2001 World Cyber Games StarCraft competition, and though he had been out of practice for a few years was still quite a good player. The match was arranged to see how well StarCraft AI bots had progressed and to see if they could actually beat a decent human opponent.

For the best-of-three match, Oriol chose his races randomly and ended up beating Skynet in a 2-0. In the first match, Oriol played Zerg vs. Skynet's Protoss on Python, a four player map. Oriol chose to start with a fast expansion strategy and transition into two base mutalisk production. Skynet chose to rush with a few early zealots, which was luckily the best possible choice given Oriol's strategy. Skynet's initial attack destroyed Oriol's early defenses, and nearly won the game in the first few minutes, however it then proceeded to send zealots to attack one at a time rather than group up its units before moving in, which allowed Oriol to catch up. Once Oriol produced his mutalisks, Skynet did not produce sufficient air defenses and Oriol quickly destroyed Skynet's base. In the second game, Oril played Terran, again on Python. After holding off early Dragoon pressure from Skynet, Oriol moved out with a few marines, medics and tanks. Skynet tried to defend with its army of Dragoons, however due to poor unit targeting decisions it started to attack useless medics after the marines had died, rather than the tanks. Oriol overcame the Dragoon army and was victorious. Later analysis of the match concluded that Skynet, while dominant over the other bots, was unable to properly adapt and transition into a mid-game strategy in game one once its early pressure failed, and in game two made a key blunder in unit targeting which cost it the game. The humans were still in command.

The 2012 competition was also hosted by the University of Alberta, with the major difference from the 2011 competition being the addition of persistent storage. Bots could now write information to disk during a match, and then read the information during other matches, allowing them to adjust strategies based on previous results. 6 of the 10 entrants used this feature to aid in strategy selection, including the top 4 finishers. More improvements to the tournament environment also meant that a total of 4240 games could now be played in the same time period. Results are shown in Table III.

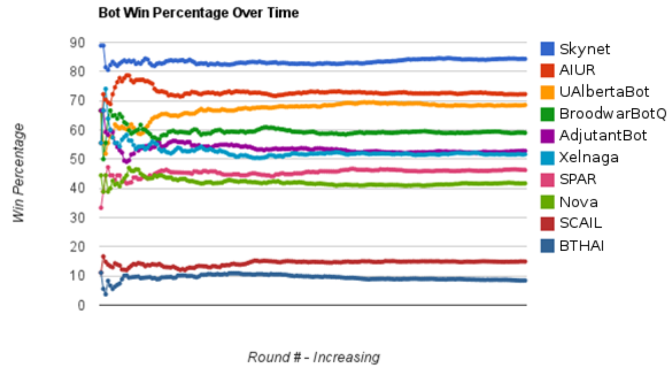

Fig. 4. Evolution of the win percentage of each bot participating in the AIIDE 2012 competition

TABLE III
RESULTS OF THE AIIDE 2012 COMPETITION.

Position	bot	win %
1	Skynet	84.4%
2	AIUR	72.2%
3	UAlbertaBot	68.6%
4	BroodwarBotQ	59.1%
5	AdjutantBot	52.8%

Skynet once again won the competition with its solid Protoss build orders and good Dragoon kiting. AIUR and UAlbertaBot switched positions from the previous year to come 2nd and 3rd respectively. Both AIUR and UAlbertaBot used data stored from the results of previous games to select a strategy for future matches. UAlbertaBot did this using the UCB algorithm, while AIUR used a uniform distribution to choose its mood before altering this distribution after some games against the same opponent to favor efficient strategies, achieving similar results than UAlbertaBot. Notice that, compared to AIIDE 2011, AIUR proposes a new mood, *Cheese*, implementing a Photon Cannon rush strategy in order to surprise the opponent and to finish the game as soon as possible. The effect of this strategy selection process can be seen Figure 4 which shows bot win percentages over time. While the earlier rounds of the tournament fluctuated wildly in results, eventually the results converged to their final values. One of the main reasons for this is due to the bots learning which strategies to use as the tournament progressed.

The 2012 man vs. machine match again used the winner of the competition (Skynet), who played against Mike Lange, aka LRM) Bakuryu. At the time of the match, Bakuryu was an A- ranked Zerg player on ICCup, and known as one of the best non-Korean Zerg players in the world. Bakuryu was considered much stronger than Oriol at the time that the match was played, and the results showed that this was true. In the first game of the best-of-three, Bakuryu made Skynet look quite silly by running around inside Skynet's base with a small number of zerglings while Skynet's zealots and half of its worked chased then in vain. After killing off several probes and buying enough time to set up his expansion, he cleaned up Skynet's army with a flying army of mutalisks. In the second game, Bakuryu contained Skynet inside its base with a group of zerglings positioned within Skynet's expansion. Skynet then constructed several Dark Templar and along with some Dragoons and Zealots attacked into Bakuryu's expansion which was heavily defended, and was crushed almost instantly, allowing Bakuryu's zergling force to finish off the Protoss base.

In this match it was shown that the true weakness of state of the art StarCraft AI systems was that humans are very adept at recognizing scripted behaviors and exploiting them to the fullest. A human player in Skynet's position in the first game would have realized he was being taken advantage of and adapted his strategy accordingly, however the inability to put the local context (Bakuryu kiting his units around his base) into the larger context of the game (that this would delay Skynet until reinforcements arrived) and then the lack of strategy change to fix the situation led to an easy victory for the human. These problems remain the main challenges in RTS AI today: to both recognize the strategy and intent of an opponent's actions, and how to effectively adapt your own strategy to overcome them.

All results, videos, and replays from the AIIDE StarCraft AI Competition can be found in[16]

B. CIG 2011

An initial attempt to run a StarCraft tournament at the Computational Intelligence in Games conference 2010 suffered from technical problems. These mainly stemmed from the desire to use evolved, largely untested maps which proved to look interesting but made the submitted bots (and/or the Broodwar Terrain Analyzer (BWTA) provided with the BWapi interface) crash so frequently that it would have been unjustifiable to announce a winner.

At CIG 2011, the tournament was therefore run with a (secret) selection of maps used in league play, which can be regarded as the most important difference to the AIIDE tournament that employed a known list of maps. The competition was organized by Tobias Mahlmann and Mike Preuss and attracted 10 bots. In addition to the ones discussed in previous sections (UAlbertaBot, Skynet, AIUR, Nova, BroodwarBotQ, BTHAI), the set also contained LSAI, Xelnaga, Protoss Beast Jelly, and EvoBot, these are shortly described in the following:

LSAI (Zerg): utilizes a heavily modified BWSAL to divide management of the units to different modules that communicate via a centralized information module. It works using a simple reactive strategy to try and survive early game attacks and macro up to a larger attack force and maintain map control.

Xelnaga (Protoss): is a modification of the AIUR bot that chooses the Dark Templar Opening in order to destroy the enemy base before defenses against invisible units are available.

Protoss Beast Jelly (Protoss): always goes for a 5-gate Zealot rush, supported by an effective harvesting strategy named power-mining (2 probes are assigned to every mineral patch, thereby needing 18 probes for 100% saturation in a normal map, prior to expanding). Gas is not mined as it is not needed for constructing Zealots.

EvoBot (Terran): employs an evolutionary algorithm for obtaining rational unit combinations and influence map techniques for deciding the strategic locations. Note that this bot was submitted in a very early version, with many of its designed features not yet fully ready.

1) First Round: As the CIG competition games were executed manually due to a lack of available software (the AIIDE program was not yet available at that time), the organizers separated the ten entries into two brackets. In each bracket of 5 bots, a round-robin tournament was held with 10 repetitions per pairing, resulting in 40 games per bot. The 5 maps chosen for the first round were selected from the pool of well-known league play maps found on the internet: *(2)MatchPoint 1.3*, *(4)Fighting Spirit 1.3*, *iCCupdestination 1.1*, *iCCup gaia*, and *iCCup great barrier reef*. Each bot pairing played on every map twice, with switched starting positions.

The two top bots of every bracket qualified for the final round. Table IV summarizes the results. Note that as BroodwarBotQ and BTHAI have the same number of wins, their direct encounter was evaluated which accounted 6:4 for the BroodwarBotQ. The bots going into the final were thus UAlbertaBot, Skynet (from bracket A) and Xelnaga and BroodwarBotQ (from bracket B). All qualified bots play the Protoss faction. Most bots proved pretty stable, only Xelnaga and Protoss Beast Jelly crashed relatively often (each in more than a quarter of the games). Crashing of course resulted in an instant win for the other bot. In some cases, neither bot was able to finish the other off completely, so that they went into a passive state. We manually ended such games after around 15 minutes and assigned victory to the bot that had obtained more points as indicated on the end game screen.

2) Final Round: The final round was played in a similar mode as each of the first round brackets, using another set of 5 previously unknown maps: *iCCup lost temple 2.4*, *iCCup rush hour 3.1*, *iCCup swordinthemoon 2.1*, *iCCup yellow 1.1*, and *La_Mancha 1.1*. Letting each pairing play on each map twice again with switching starting positions resulted in 30 games per bot. The final results are displayed in table V, indicating Skynet as winner and UAlbertaBot as runner-up, being almost equally strong, and the two other bots as clearly inferior.

VI. Open Questions in RTS Game AI

As illustrated in this paper, there is a set of problems in RTS game AI that could be considered mostly solved, of for which we have very good solutions. One example of such problems is pathfinding (mostly solved) or low-scale micro-management (for which we have good solutions).

However, there are many other problems for which this is not the case. For example, there is no current Starcraft bot

[16]http://www.StarCraftAICompetition.com

TABLE IV
RESULTS OF THE FIRST ROUND AT CIG 2011, HELD IN TWO BRACKETS. QUALIFIED FOR THE FINAL ROUND: UALBERTABOT AND SKYNET (FROM A), XELNAGA AND BROODWARBOTQ (FROM B, THE LATTER BY COMPARING DIRECT ENCOUNTERS WITH BTHAI OF WHICH 6:4 WERE WON).

Bracket A				Bracket B			
Crashes	games	bot	wins	Crashes	games	bot	wins
0	40	UAlbertaBot	33	12	40	Xelnaga	25
1	40	Skynet	31	3	40	BroodwarBotQ	23 (6)
2	40	AIUR	24	0	40	BTHAI	23 (4)
1	40	Nova	8	17	40	Protoss Beast Jelly	17
0	40	LSAI	4	0	40	EvoBot	12

TABLE V
RESULTS OF THE CIG 2011 FINAL ROUND.

Crashes	games	bot	wins
0	30	Skynet	26
0	30	UAlbertaBot	22
3	30	Xelnaga	11
2	30	BroodwarBotQ	1

that can come up with its own tactical moves, such as “unit drops”. Some bots do drops, but only if this is hard-coded; no bot has the capability of reasoning about the current situation, synthesize a tactical move that involves a “unit drop”, and determine that this move is the best one in the current situation. This is related to the lack of real-time adversarial planning techniques that scale up to the size required for RTS games. Similarly, current bots do not exhibit adaptation to opponent strategies. Some switch between different build-orders, but do not fully adapt their strategy. No bot is capable of observing the opponent and autonomously synthesize a good plan from scratch to counter the opponent strategy.

We present here a list of problems that are currently unsolved, grouped in various categories.

- **Learning and adaptation:**
  - Adaptation to opponent strategy: observing the opponent strategy, and synthesizing an adequate counter strategy. Current bots switch between predefined strategies based on hard-coded preconditions, or based on the performance of each predefined strategy against an opponent in previous games, but no current bot creates new strategies (like Chess or Go playing programs do).
  - Learning from experience in RTS games: how can we make a bot that improves performance over time? some current bots learn which strategy (out of a predefined set of strategies) is best against a given opponent, but how can we devise learning strategies that can perform more general learning?
  - Learning from observation (from demonstration, or from observing the opponent) in RTS games: how can we learn by observing the game play of other players? can we devise algorithms that can automatically extract strategies from observation, and later apply them?
- **Planning:**
  - Adversarial planning under real-time constraints: although some solutions for small-scale real-time planning have been recently proposed (such as [**?**], based on alpha-beta game-tree search), the problem of large-scale adversarial planning under real-time constraints is still open.
  - Adversarial planning under uncertainty of partially-observable domains: how can we adapt adversarial planning techniques for dealing with uncertainty? This problem has been widely studied in the context of simple games such as back-gammon [**?**], or Poker [**?**]. However, the techniques developed for those domains do not scale to RTS-game scenarios.
  - Adversarial planning with resources: similarly, even if there exist planning algorithms that handle resources (like GRT-R [**?**]), they cannot scale up to the size of problems needed for RTS games like Starcraft.
- **Integration:**
  - Multi-scale planning/reasoning: as described in this paper, all the bots developed for the Starcraft AI competitions decompose the problem of playing an RTS game into smaller subproblems, and then solutions for each of those subproblems are integrated in to a common architecture to play the game. However, the integration of each of the modules in a unified architecture is still an open problem. For example, how can decisions made at high-level modules be integrated with decisions made at lower-level modules?
- **Domain Knowledge:**
  - We know how to incorporate some aspects of domain knowledge (e.g. build orders) into RTS game playing agents. But, in general, how to incorporate some forms of domain knowledge into algorithms for RTS games is still an open problem. For example, standard techniques to encode strategies for other forms of games, like Behavior Trees, are hard to deploy in

RTS games. Is it possible to devise techniques that can automatically mine the existing collections of domain knowledge for an RTS game like Starcraft, and incorporate it into the bot? An initial exploration of this idea was carried out by Branavan et al. [?]

VII. Empirical Evidence of What is Missing in Existing Bots

Here, whatever experiments we want to include to support which aspects of RTS Game AI require more work.

VIII. Discussion and Conclusions

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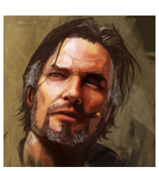

Jim Raynor Jim Raynor was a Confederate marshal on Mar Sara at the time of the first zerg incursions on that world. He is now with Raynor's Raiders Inc.