ONLINE CRITICAL GAME FLOW AND DYNAMIC ROLE ASSIGNMENT BASED ON POTENTIAL FIELDS

A THESIS SUBMITTED TO
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
OF
THE MIDDLE EAST TECHNICAL UNIVERSITY

BY

AYTUNÇ AYHAN

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR
THE DEGREE OF MASTER OF SCIENCE
IN
ELECTRIC-ELECTRONIC ENGINEERING

DECEMBER 2004

Approval Graduate School of Natural and Applied Sciences

____

Prof. Dr. Canan Özgen
Director

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science

____

Prof. Dr. İsmet Erkmen
Head of Department

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality as thesis for the degree of Master of Science

______________________	______________________
Prof. Dr. Aydan Erkmen Co-Supervisor	Prof. Dr. İsmet Erkmen Supervisor

Examining Committee Members

Prof. Dr. Aydın Ersak	(METU,EE)______________________
Prof. Dr. İsmet Erkmen	(METU,EE)______________________
Prof. Dr. Aydan Erkmen	(METU,EE)______________________
Assoc. Prof. Dr. Aydın Alatan	(METU,EE)______________________
Prof. Dr. Tuna Balkan	(METU,ME)_____________________

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last Name :Aytunç Ayhan

Signature:

ABSTRACT

ONLINE CRITICAL GAME FLOW AND DYNAMIC ROLE ASSIGNMENT BASED ON POTENTIAL FIELDS

Ayhan, Aytunç

M.S. , Department of Electric-Electronic Engineering

Supervisor : Prof. Dr. İsmet Erkmen
Co-Supervisor: Prof. Dr. Aydan Erkmen

December 2004, 71 pages

This thesis describes the critical game flow and dynamic role assignment based on potential fields in robot soccer game and actions taken depending on role assignment. Role assignment is a standard problem of multi-agent game system like robot soccer and it can be realized by many techniques. In this thesis, game flow is described dynamically in terms of critical zones which are formed by potential fields based on the field environment as hills and valleys.

Keywords: Game flow, Role assignment, Multi-agent coordination

ÖZ

SÜREKLİ KRİTİK OYUN AKIŞI VE POTANSİYEL ALANA BAĞLI OLARAK ROL DAĞILIMI

Ayhan, Aytunç

Yüksek Lisans, Elektrik-Elektronik Mühendisliği Bölümü

Tez Yöneticisi : Doç. Dr. İsmet Erkmen
Ortak Tez Yöneticisi: Prof. Dr. Aydan Erkmen

Aralık 2004, 71 sayfa

Bu çalışma, küçük boyutlu robotlar arasında oynanan futbol oyununda potansiyel alanlara bağlı olarak kritik oyun akışını ve rol dağılımını ve rol dağılımına bağlı olarak robotların eylemlerini anlatır. Rol dağılımı olayı robot futbolu gibi çok oyunculu sistemde temel sorunlardan biridir ve birçok yöntemle incelenebilir. Tez içinde oyun akışı, dinamik biçimde oyun ortamına bağlı olarak potansiyel alanlar tarafından vadiler ve tepeler şeklinde oluşturulan kritik bölgelerden dolayı meydana gelir.

Anahtar Kelimeler: Oyun akışı, rol dağılımı ve robotlar arasında koordinasyon

ACKNOWLEDGMENTS

Firstly, I would like to express my gratitude to my advisor Prof. Dr. İsmet Erkmen and my co-advisor Prof. Dr. Aydan Erkmen for their powerful guidance, support and motivation throughout my research. They provided counsel, and assistance that greatly enhanced my studies.

I also would like to thank to my colleague, Kerim Koncagül who gives some tips on preparing my thesis and thank to my friends including Derya Aydemir, Fazlı Öztürk, Bülent Ali Yıldırım, Hakan Koçyiğit, Mehmet Kasapoğlu for their patience and support during the master’s period.

Finally, I would like to thank to Özgül Fidan who gives support in terms of software as well as documents and to my parents for everything.

TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

CHAPTER 1

INTRODUCTION

1.1 Objectives

Robotsoccer [1-2-3] is a rich research domain where wide range of methodologies and technologies need to be integrated involving multi-agent collaboration, strategy building, real-time planning, strategic decision making, intelligent robot control with high performance machine learning module adapting to different strategies in an effective manner. The thesis investigates cooperation of a team competing against an opponents' strategic cooperation in order to score a goal in an uncertain and dynamic environment and rather than the development of individual strategies among robots, focuses on a game flow of strategies to shape the player actions.

In robot soccer application, players of each team must collaborate in order to place, after a series of strategic moves, the ball in the opposing goal while at the same time defending their own goals against opponent strategic game activities, by creating game flows of several levels of criticality. Therefore a soccer game can be modeled as the dynamical changes of these critical regions where the spread of the most critical region toward the goal and how frequent such a spread occurs would represent the efficiency of the attacks occurring with the game flow.

In this thesis, one of the main objective is to model the critical game flow which results from the multiple strategies between two adversary teams during the evolution of the game. However, generation of team strategies that vary dynamical according to what the opponent offers as its own strategy is quite challenging. Thus how to use the model of the critical game flow instead of tracking strategic changes of the opponent and how to handle successfully the opponent strategic play is the main concern of our work

Within the game environment, players changing their positions according to dynamical strategic game flow against the strategic perturbation of the opponent must select the right actions [4-5-6]. In order to select the right actions, players should assume the most suitable roles. Role assignment in a soccer game focuses on how players act according to various strategic situations such as offence, defence and intercept.

For an effective team coordination, the role assignment [7-8-9] is a critical issue and should be performed well. Different role assignment in a dynamic decentralized multi-agent competitive cooperation would result in totally different game flow displaying totally different strategic interplay.

1.2 Motivation

In the existing literature, robot soccer applications deal separately with obstacle avoidance, role assignment and multi-agent coordination. Then, performances are all combined to create a dynamically changing team strategy. To unveil opponent game strategy and build one's own defence and offence strategic play online under many uncertainities is a rather complex task that critically influence the game performance. Instead of trying to unveil and predict individual strategies that vary overtime and space, trying to model the two team interplay of strategies as a game flow and globally act with the game flow to change its spread and shape in a certain way would be to act with a global picture and would be a more attractive and more efficient and elegant approach. Thus, the application of this approach to robot soccer would be naturally simple and the adaptation would come naturally since we as human are more used to watch and analyse soccer as a game flow from our spectator status. In addition, our approach would naturally respond to online game flow changes reflecting the strategic interplay changes of each team without the need to focus on those individually.

1.3 Goals

In this thesis, rather than generating individual strategies and their changes, team strategies are modeled as a dynamically changing critical game flow applied to robot soccer game that has not been generated previously. Role assignment need to be generated from the current state of the game flow and actions should be derived from it in order to change the game flow in a favorable way increasing hills for opponent creating valleys for own players, ball and goal site for winning. Performance of approach need to be applied and we test our approach in a robot soccer game will be further suitable for Sony AIBO robot soccer game [10-11].

Players need to assume specific roles according to strategic situations but without the need to generate those individual situations and should be able to switch their roles in order to maximize the performance of team coordination. Therefore, roles need to be assigned dynamically to players according to their position on the game field within the game flow modeled so that the player being closest to the most critical region of the game is assigned the most active role according to the players proximity to the most critical region of the game flow, the other roles need to be distributed considering their priorities based on proximity to criticality.

Players holding specific roles behave on the game field based on their role, thus generating different actions that yields changes of the critical game flow. Player having the most active role in the most critical region of the game flow will be the is most important player to change the game flow and the destiny of the play. Roles of players should be ranked according to their criticality position within the game flow and players that assume less degrees of the criticality should assume supportive roles to the most critical player.

1.4 Methodology

The balance of this thesis focuses on the modeling methodologies for determining the critical game flow and on the assignment of roles dynamically online, according to where the players are with the critical game flow. We call this game flow embedded role assignment.

Our initial consideration is to generate the game flow model according to the discrete strategic situations of offence, defence and intercept. The model should also incorporate the target critical game zones which are the goals and the ball.

The potential field approach quite fits naturally to the concept of a game flow model. We developped the potential field model of a critical game flow with nested regions of criticality.

As a second step, the role assignment is done dynamically according to the position of players in the critical zones of the game flow. Players near the critical zone are assigned leading role taking precedence over others and taking actions that radically changes the game flow of the upcoming steps. In the potential field approach, the critical zones are represented by valleys, and players placed in the surroundings of valleys assume more important tasks, since those players are able to realize these tasks more effectively than others due to their proximity to the critical regions.

Lastly, actions are mapped to roles and strategic situations are a determining factor characteristic of robot actions. In the offence situation, the attacking team tries to expand the critical regions around opponent goal or keep the critical regions there as long as possible. To do this, attacking players try to bring the critical regions to the neighbourhood of the opponent goal site by creating valley of potential fields while opponent players try to create obstacles which are considered as peaks of potential fields. The players having more critical roles and placed in the critical region undertake the most striking actions by changing the critical game flow in favor of the attacking team such as to bring the ball to the opponent field. When the team is defending, this time the team tries to create peaks for the opponent players. In the defence situation, the most critical zone is around the ball, thus immediately the region needed to changed into a peak is the region around the ball by increasing repulsive effect in this region at potential fields. For intercept situation, similar methods to especially defence situation are applied to obtain the ball.

1.5 Outline of the Thesis

The content of this thesis is organized as:

Chapter 2 introduces the literature survey for role assignment, team coordination and strategy acquisition for robot soccer game, including leading papers and thesis works on the relevant topic. In this chapter we also introduce the comparative performance analyses of each existing method to motivate our thesis work and enhance the impact our contribution done in this field.

Chapter 3 firstly dwells with the mathematical background needed on potential fields and develops our game flow model with the different levels of criticality based on this potential field approach designed. The chapter finally describes how dynamic role assignments are done based on potential values of players positions on the game field.

Chapter 4 demonstrates our approach by simulation results of dynamic role assignment at a robot soccer game for three strategic situations and it is tested with a simulator realizing a robot soccer match.

Chapter 5 conducts performance analyses of our approach a simulation results, also developping necessary performance measure.

Chapter 6 concludes the thesis work also providing suggestions for future work.

CHAPTER 2

REVIEW

This section presents a short survey related to the main features of robot soccer games together with the methodologies used about methods that have been used. The mathematical background also necessary for our proposed method is also mentioned briefly here.

2.1 Obstacle Avoidance and Real Time Planning

Obstacle Avoidance and Motion Planning are both necessary components for any robotic locomotion task. Obstacle Avoidance refers to planning collision-free trajectories for robotic systems while real time planning refers to planning smooth mobility for robotic systems. This section dwells with existing approaches aiming at solving these problems of robot locomotion.

2.1.1 Cell Decomposition

The cell decomposition approach is based on decompositing the free configuration space into cells, where a cell is a convex polygon. Succeeding cell decomposition partitionning the free space into connected regions or cells, a connectivity graph is constructed which cells as vertices and edges being connections among neighbouring cells. Finally a minimal path is searched within this connectivity graph. If the initial position and the final position of the robot falls into the same cell, then the path-finding process is trivial.

Cell decomposition method can be applied to robot soccer as depicted in Figure 2.1. In Figure 2.1 a robot reaches the target by decomposing the game field into cells of predefined shape, such as squares and by finding the shortest path. Since robot soccer system needed to survive in a highly dynamic environment in which robots move fast and information of robots and the ball are delivered with a frequency between 30 Hertz and 60 Hertz, this method usually has not been prefered. Woltinge [12] have proposed an approach about this problem, and also has summarized some motion planning approaches and their characteristics.

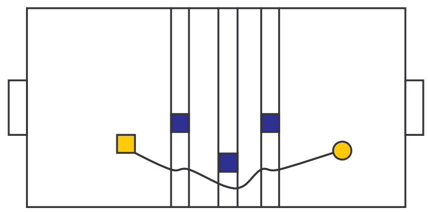


Figure 2.1 Cell decomposition's application to robot soccer

Probabilistic Cell Decomposition(PCD) as a method for path planing in context of manipulation planning is investigated by Lingelbach [13]. This method shows that considerable performance improvements can be gained when adapting parts of the PCD algorithm to a specific manipulator.

2.1.2 Limit Cycle Navigation

Limit cycle method is based on 2nd-order non – linear system.

$$\dot{x}_2 = x_2 + x_1 * (1 - x_1^2 - x_2^2)$$

$$\dot{x}_1 = -x_1 + x_2 * (1 - x_1^2 - x_2^2) \qquad (2.1)$$

This equation represents the periodic orbit of Figure 2.2

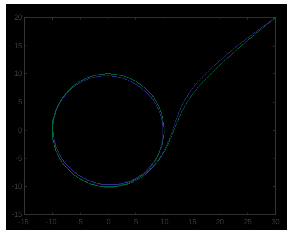


Figure 2.2 Periodic orbit of limit cycle

This method is directly applied to a robot operating in a dynamically changing environment such as in a soccer robot system by Kim [14]. By adjusting the radius of the motion circle, and the direction of obstacle avoidance, the navigation method, enables a robot to maneuver towards a desired target. Limit cycle method does not calculate all trajectories in the current situation, but only calculates the next trajectory of the robot using the robot's current relative positions of the target and any obstacles as reactive approach. This method generates the navigation plan incrementally and adapts to the dynamically changing environment

Limit cycle method has advantages over other methods such as notably potential fields method, by guaranteeing the removal of local minima. It is an effective methodology in avoiding collision with moving around obstacles.

2.1.3 Roadmap method

Roadmaps(Figure 2.3) are constructed as a connectivity graph with vertices representing configurations sampled randomly and edges corresponding to connections between nearby vertices. Roadmaps are queried to find a path for a given motion planning task where configurations leading to possible collision with obstacles are removed.

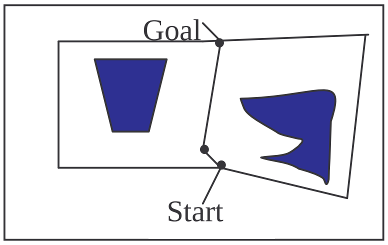


Figure 2.3 Example roadmap method

Lavraki and Sventsk [15] have proposed a two-phase method to solve robot motion planning problems in static workspaces. In the learning phase, the method constructs a probabilistic roadmap as a collection of configurations randomly selected across free space. In the query phase, it uses this roadmap to process quickly path planing queries, each specified by a pair of configurations.

Amato and Dale [16] have also proposed probabilistic roadmap motion planning methods, this study seems significant, scalable speedups can be obtained with relatively little developer effort for motion planning and identifying potential difficulties that might be faced in other efforts to parallelize sequential motion planning methods.

Lavraki and Latombe [17] has analysed randomized preprocessing scheme that has been used for query processing in robot path planning. This study involves a new randomized algorithm for determining connected components

2.1.4 Potential Fields Method

For path planning targets may be thought of as attraction points and obstacles as repulsive areas. Potential field approach model environmental effects in a such manner, where the goal or target location has the lowest potential attracting the robot while obstacles have the high potentials pushing away.

A major drawback to this approach, is the keeping into local minima which prevents the robot from attaining its goal.

One of the earliest obstacle avoidance algorithms was proposed by Khatib [18] and have since been widely used in the mobile robotics community for tasks such as local navigation and obstacle avoidance. In this method, obstacles exert repulsive forces, while the target applies an attractive force to the robot. A resultant force vector comprising the sum of a target-directed attractive force and repulsive forces from obstacles, is calculated for a given robot position. With resultant force vector as the accelerating force acting on the robot, the robot's new position for a given time interval is calculated, and the algorithm is repeated.

Nam, Lee, and Ko [19] focused on avoiding moving obstacles using the same potential field approach. At each instance, the accessible region that is being swept by an obstacle in the next time step is conservatively estimated from the velocity, acceleration and dynamic constraints of the obstacle. The repulsive potential field for the obstacle is then constructed around these accessible regions. The biggest improvement (strength) of this algorithm is the ability to account for obstacle motion throughout a complete time step by estimating the swept area.

Cho and Kwon [20], in their paper, introduce an improvement to Khatib’s method in order to eliminate the local minima problem by introducing a velocity potential function, based on potential flow theory in hydrodynamics. Potential fields are also combined as a hybrid to other methods.

Borenstein [21-22] combines a histogram grid world model with the concept of potential fields for obstacle avoidance. A robot navigated along a potential fields may oscillate at local minimum. This method prevents tendency of robot to oscillate inherent to potential fields.

2.2 Multi-agent Collaboration or Cooperation

It is impossible for an individual agent to reach the team goal site alone when pressed by an adversary team. Individual agents in a team must do coordinated actions under a certain strategy and carry out decisions that work toward the team goal.

2.2.1 Market-Driven Method

The main goal in free-markets is maximizing the overall profit of the system by individual profit uses of each participant. The idea of the market-driven method for multi-robot teams is based on the interaction of the robots among themselves in a distributed fashion for trading work, power and information. The overall goal of the system is decomposed into smaller tasks and an auction is performed for each of these tasks. In each auction, the participant robots (which are able to communicate among themselves) calculate their estimated cost for accomplishing that task and offer a price to the auctioneer. At the end of the auction, the bidder with the lowest offered price is given the right of execution of the task and receives its revenue on behalf of the auctioneer. A robot may open another auction for selling a task that it has won from another auction; two or more robots may cooperatively work and get a task which is hard to accomplish by a single robot.

The pioneering on the market-approach for multi-agent cooperation is the one by Dias and Stenz [23]. It is highly robust and avoids single point failure, while increasing the team performance considerably.

A market based algorithm proposed for multi-robot coordination in robot soccer games is developped by Kose et al. [32]. There, each player in the soccer game calculates the costs for its assigned task, then searches for another teammate who can do this task for a lesser cost. If one or more of the robots can do this task with a lower cost, they are assigned to that task, so both the robots and the team increase their profit. Other robots take actions according to their cost functions. Since all robots share their costs, they know which task is appropriate for each one so they do not need to tell others about their decisions.

There are other approaches on multi-agent driven method using utility or cost functions. Spaan [25-26] use utility functions for assigning roles to players in robot soccer. Each role has its utility function which tries to measure how well suited a robot is for this role in the current state of the world. This measure is based on the time a robot expects it needs to reach the ball, how well the position of a robot is suited for the role and whether or not a robot has possesion of the ball.

2.2.2 Potential Fields Approach

Besides obstacle avoidance and motion planning, potential fields approaches are also used for multi agent cooperation and action selection. Most of them model the environment into cells of a fixed size [27] and compute the potential value of each cell for determining the most appropriate position. A quite different approach is the Electric Field Approach [28] applied in RoboCup domain. Positive and negative electric charges are attached to the relevant objects in the agent's domain, and resulting electric field is used to estimate the heuristic value of a given configuration. This value is used to select the action that results in the best configuration.

Carrying out decisions as to the robot's next action and using the potential fields to determine locations of robots undertaking those actions is a methodology proposed by Tews [29]. The generated system is based on a combination of potential fields assigned to field position and the position of the robots. The first aim of the system is to find a good location for the ball that might reasonably be achieved with a single kick from its current location. The evaluation begins with a base potential field that contains values that indicate the desirability of the ball at each location for an empty field. The robot potential fields are then superimposed to the base field in order to create a total potential fields. Teammate robots form potential valleys, while opposing robots form potential hills. Further features such as the distance to the ball, or whether the cell is in a clear path to the robot are also used to create the potential fields. In Figure 2.4 it is seen how suitable shoot position is determined. The Figure 2.4 shows the resulting potential field for determining the kicking coordinates with the opposition players in the configuration shown in the diagram on the right. The opposition goal is on the right hand side. Darker areas represent high values as can be seen from the overlapping region between two of the players creating the largest peak in the figure. The white areas show the most favourable areas to kick the ball. From this potential field, the lowest value stands at the bottom of the opposition goal.

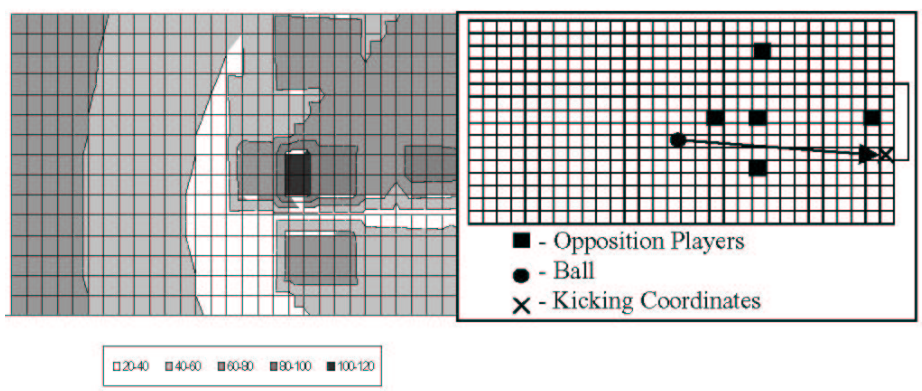


Figure 2.4 Example of kicking potential field

Vail & Veloso [30] used the shared potential fields to solve the role assignment and coordination problem. The potential fields were based on the positions of the other robots on the team and the ball. The robots positioned themselves on the field by following the gradient to a minimum of the potential field. In principle, potential functions can be applied to any multi-robot domain. Robots perform distributed task allocation by calculating their suitability for a task and broadcast this suitability as a bid to their teammates. The robot with the highest bid wins the task. If the winning robot becomes unavailable some reasons, the robot with second highest bid wins the task.

Since, the potential field is the sum of several linear components such as repulsion terms from the walls and other robots, depending on their role, robots may use different subsets of the field components and potential fields should fulfill certain strategies in their design.

Indeed, potential fields for soccer game are designed such that local minima arise at positions from which the robots can support the player trying to score a goal. For that "support" player, the field guides the robot to a good position for receiving passing or recovering the ball if the shooting of the ball to the goal site fails. For a defensive player, the gradient of the potential fields guides the robot to a position where it blocks its own goal and can recover the ball in an intercept situation with the opposing team.

2.2.3 Genetic Programming Approach

Genetic programming(GP) is a promising new method for automatically generating functions and algorithms through natural selection. The goal of this method is to generate programs for the cooperation of autonomous agents. GP methods attempt to evolve collective behavior immediately from primitive actions. More realistic tasks require several emergent behaviors and a proper coordination of those is essential for success. In contrast to other learning methods, the automatic programming of genetic algorithms makes it a natural approach for developing algorithmic robot behaviors.

Genetic programming is a domain-independent method that genetically breeds a population of computer programs or algorithms to solve some task. These algorithms are known as genomes. Genetic programming optimizes the program trees formed from atomic functions. An example the GP tree as designed by Luke [31] for robot soccer is shown in Figure 2.5. Each node in the tree is a function, which takes as arguments the results of the children to the node.

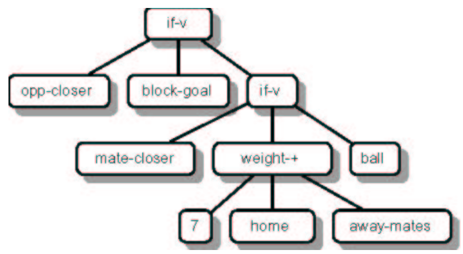


Figure 2.5 A typical genetic programming tree [31]

The user supplies the genetic programming system with a set of atomic functions with which genetic programming may build trees. Additionally, the user provides an evaluation function, a procedure which accepts an arbitrary genetic programming genome tree, and returns an assessed fitness for this genome. The evaluation function assesses the fitness of a tree by executing its code in a problem domain.

The methodology of genetic programming system begins by creating a large population of random trees for its first generation. It then uses the evaluation function to determine the fitness of the population, selects the more fit genome trees, and applies various breeding operators, such as crossover and mutation operators, to them to produce a new generation of trees. It repeats this process for successive generations until either an optimally fit genome tree is found or the user stops the genetic programming run.

There are other genetic programming approach to robot soccer [32-33]. In Aransson's work genetic programming is used to teach software robots to play soccer and to investigate the development of multi-agent strategies. The robots quickly learn to chase and kick the ball towards the goal or pass it to a teammate.

Zhang and Cho have introduced a framework, called fitness switching, that facilitates evolution of composite emergent behaviors using genetic programming. In fitness switching, different parts of a genetic tree are responsible for different behaviors and for each of the subtrees a basis fitness function is defined. The complex behavior is produced by dynamically changing fitness types from a pool of fitness functions. Coevolutionary fitness switching described in this chapter is an extension of fitness switching in which multiple subtrees are coevolved in a single GP run.

The major drawback of genetic programming is not suitable for swift decision and online problems because it is relatively slower than the other methods.

2.3 Online Learning

The goal of online learning is to enable multiple agents to learn suitable behaviors in a dynamic environment and to create cooperative behavior among the agents without any prior-knowledge. Consequently online learning is a critical issue in robot soccer games. One methodology frequently one used for multi agent system is reinforcement learning.

2.3.1 Reinforcement Learning

Reinforcement learning addresses the question of how an agent that senses and acts in its environment can learn to choose optimal actions in order to achieve its goals. Individually, each robot learns to select the best behaviour for each state.

The main advantage of reinforcement learning is that it provides a way of programming agents by reward and punishment without needing to specify how the task is to be achieved. On each step of interaction the robot receives an input that normally provides some indication of the current state of the environment. The agent then chooses an action to generate as output. The action changes the state of the environment and also provides the robot with a reward of how well it performed. Finally the agent should choose actions that maximise the long-run sum of rewards.

Kostiadis [34]'s work addresses decision-making and cooperation problems by using reinforcement learning techniques. By gathering useful experience from earlier stages, an agent can significantly improve its performance. The method used requires no previous knowledge regarding the environment.

Multi agents games like Pursuit Game where there exist multiple preys and multiple hunters is solved by using reinforcement learning method [35].

Disadvantages of reinforcement learning is that for realistic applications, the size of the state space is so large that learning takes too much time to be practical, and the system can start learning about the sequence of actions leading to that reward only when a reward is received, as a result it takes a lot of time to learn long action sequences.

In this thesis, we opt in our work to model the interplay of the two team strategies during the game as a dynamically changing critical game flow with patterns in multiple resolutional levels of criticality by using potential fields method instead of generating individual strategies and their changes as it is the case in those references.

CHAPTER 3

MODELING DYNAMIC GAME FLOW

3.1. The Dynamic Game Flow

A dynamic game flow in a two team game is generated from the interplay of strategies between two adversary teams displaying criticality levels which vary according to situations a team creates in order to score. In this work, the critical game flow is modeled using potential fields for three strategic situations in which the two teams find themselves involved in: offence, defence, intercept. Each situation receives a different potential distribution according to where on the game field different potential functions enter in action such as the goal field, the ball field, the opponent players field, the teammate player field and the wall field, the auxiliary field.

The decision on offence, defence and intercept is made from the point of view of a home team possessing the ball or not and where on the game platform. Of course, a team having the ball on the opponent portion of the platform creates an offence situation, if the team does not possess the ball and the opponent has it, it is in the defence situation. The other situation where neither team has the ball is called the intercept situation.

3.2. Potential Fields : a quick overview

A potential field is a vector space with attractors and repellers. Goals attract, generating attractive forces on every point of the soccer field and obstacles such as other players, walls, e.g. repulse generating repulsion forces.

The attractive potential such as proposed in Khatib [18] induces an attractive force whose intensity is a linear function of the distance between the robot and the goal. With such a potential, the robot behavior with respect to the obstacles strongly depends on its distance to the goal: for instance, the robot tends to dangerously approach the obstacles when it is far from the goal. Most of the proposed repulsive potential functions in the literature only depend on the distance to the obstacles. Some repulsive functions have influence limit distance over which the obstacle has no influence on the robot motion such as Equation 3.3. At this equation for the values below ρ_0, the potential field affects surroundings objects.

$$U(x) = U_a(x) + U_r(x) \tag{3.1}$$

where $U_a(x)$ is the attractive potential produced by the goal at x, and $U_r(x)$ the repulsive potential induced by the obstacles at x. The resultant force F is then:

$$F(x) = F_a(x) + F_r(x) \tag{3.2}$$

where $F(x) = -\vec{\nabla} U(x)$. $F_a(x)$ is the attractive force which guides the robot to the goal and $F_r(x)$ is the repulsion induced by the obstacles. Once computed, the force F(x) is then simply transformed into a robot motion command.

$$\begin{aligned} U(x) &= (1/\rho - 1/\rho_0)^2 \qquad && \rho < \rho_0 \\ U(x) &= 0 && \rho > \rho_0 \end{aligned} \tag{3.3}$$

The force vector at any given robot position is computed by summing all the forces exerted on that vector. A robot would move through this world towards the goal by following vectors primarily influenced by the goal position. If the robot encountered an obstacle, it would be pushed away from the obstacle by vectors primarily influenced by the obstacle, until it moved around the obstacle and could again move towards the goal (Dudek and Jenkin [36] 138-140).

3.3 Coloring of Potential Fields

For pictorial purposes potential functions are discretized over 70 criticality levels represented by a different color. Whereas the blue color is assigned to the higher potential with the lowest criticality, the red color is assigned to the lowest potential, the attractor with the highest criticality value. Figure 3.1 gives the color legend for the criticality scale used in a critical game flow results, showing all colors used for design of potential fields from the lowest potential value representing with hot color to the highest potential value representing cold color.

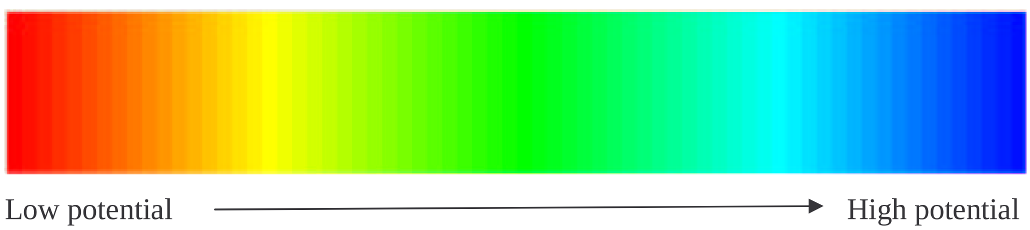


Figure 3.1: Colour spectrum for potential fields

3.4. Situation Based Dynamic Critical Game Flow Model (CGF)

3.4.1 CGF Under Offence Situation

This situation presents itself as one team possessing the ball and trying to push the game flow toward the opponent field by their moves. The game flow in this situation is the resultant of several potential fields in different strategic regions of the game. We distinguish here, the following strategic regions of the game flow which different potential fields are designed.

• **Goal Field:** This field tries to take the robot closer to the opponent goal , making it an attractor for the robot as represented by the following function, since it is able to create the opportunity of scoring:

$$pf_g(x,y) = k_g * \sqrt{(x - x_{goal})^2 + (y - y_{goal})^2} \tag{3.4}$$

where x and y are the coordinates of the play-field and x_{goal} and y_{goal} are coordinates of the goal, k_g is the amplitude parameter. Equation 3.3 is a quadratic function in the goal neighborhood and an asymptotic linear behavior away from it. Throughout this thesis, this type of function is used for attractive functions.

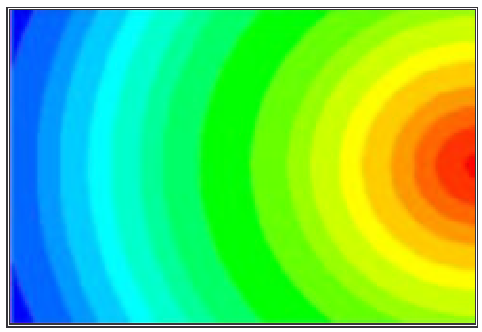


Figure 3.2(a): Potential goal field for offence at 2-D

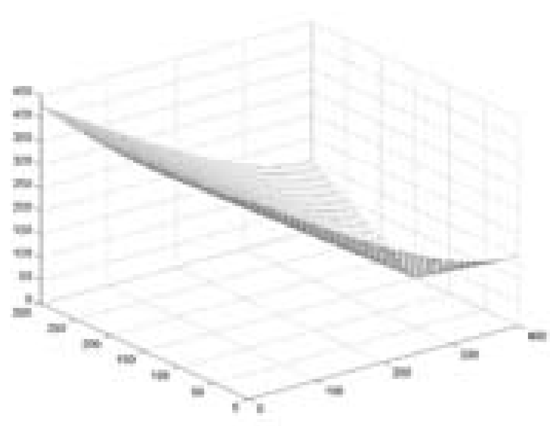


Figure 3.2(b): Potential goal field for offence at 3-D

Figure 3.2(a) depicts the goal field in colour scheme. The changes from blue to red towards the opponent field depicts a game flow with criticality towards the opponent goal area. Figure 3.2(b) shows 3-D graph of the potential fields. The valley and peak for goal field can be seen easily from the graph. According, at the graph, critical valley naturally occurs towards the opponent goal.

• **Ball Field:** This potential field tries to bring the robot closer to the ball, making the ball an attractor, since the hottest strategy is to get the ball by the function:

$$pf_b(x, y) = k_b * \sqrt{(x - x_{ball})^2 + (y - y_{ball})^2} \tag{3.5}$$

where x_{ball} and y_{ball} are coordinates of the ball and k_b is the amplitude parameter. The choice of k_b affects the closeness of the players to the ball during the motion of the players. Equation 3.5 resembles Equation 3.4 from the perspective of creating an attractive region.

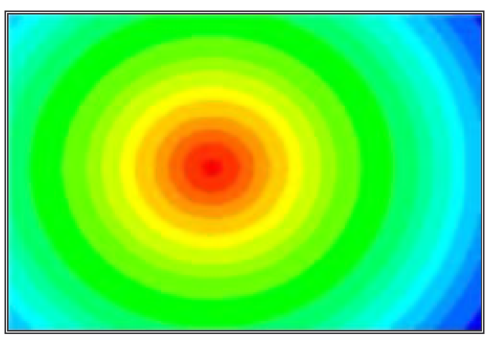


Figure 3.3(a): Potential ball field at 2-D

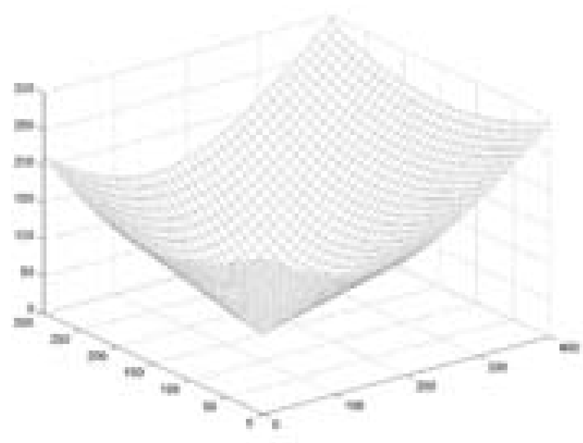


Figure 3.3(b): Potential ball field at 3-D

Figure 3.3(a) in colored scheme shows that there is a flow towards the ball. As it is seen from the graph, It forces players to possess the ball and gain control of it during the game. Figure 3.3(b) shows the 3-D sight of ball field. The position of ball creates a valley that attracts the robots with dissipative energy towards this minimum.

• **Opponent Player Field:** The purpose of this potential field is to avoid collisions with other players and thus to create a repulsive field around players are thus assigned high potential to points very close to other players of opponent team based on the formula:

$$pf_{op}(x, y) = \frac{k_{op}}{e^{b*\sqrt{(x-x_{op})^2+(y-y_{op})^2}}} \tag{3.6}$$

where x_{op} and y_{op} are the coordinates of the opponent players and k_{op} is the amplitude parameter, b is an exponential parameter. The parameter b determines the size of repulsive region. If the parameter b decreases, the areas of repulsive region gets larger.

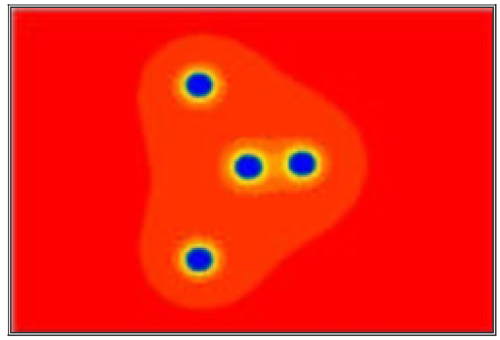


Figure 3.4(a): Potential opponent player field at 2-D

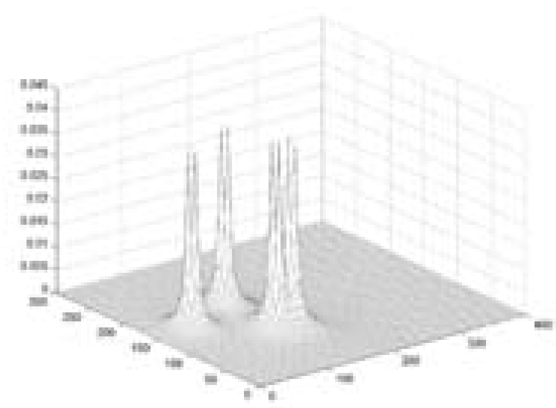


Figure 3.4(b): Potential opponent player field at 3-D

Figure 3.4(a) shows colored potential fields for opponent players. The blue areas depict repulsive regions. Figure 3.4(b) shows clearly the 3-D visualization of obstacles, the peaks surrounding the position of opponent players.

• **Teammate Player Field:** This field enables the players of the home team not to collide with each other. It creates a repulsive field around the teammate player for certain limiting distance. Its formula is designed as:

$$pf_{team}(x,y)=\begin{cases}\dfrac{k_{team}}{e^{b*\sqrt{(x-x_t)^2+(y-y_t)^2}}} & \sqrt{(x-x_t)^2+(y-y_t)^2}<d\lim it\\ 0 & \sqrt{(x-x_t)^2+(y-y_t)^2}>d\lim it\end{cases} \qquad (3.7)$$

where x_{op} and y_{op} are the coordinates of the opponent players and k_{op} is the amplitude parameter, b an exponential parameter and d_{limit} is the limiting distance. For the larger values than d_{limit} , no repulsive field will be active for a given home team player.

The graph of teammate player potential field resembles the opponent player one. At this time, peaks are formed by home team players.

• **Wall Field:** This field prevents the players to collide into surrounding walls of the game platform. It creates a linear repulsion from the wall,

$$pf_{wall}(x,y)=\max(0,c_{wall}-(y-y_{wall})) \qquad (3.8)$$

where y_{wall} is position of wall and c_{wall} is the base potential representing the maximum value of the potential wall field when robot is at the wall. By this equation, particular fields (e.g. near the wall) have linear repulsive potential fields.

Figure 3.5(a): Potential wall field at 2-D

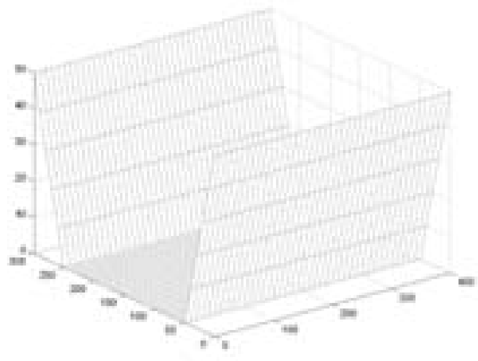


Figure 3.5(b): Potential wall field at 3-D

Figure 3.5(a) shows the linear repulsive effect of the avoided surrounding the wall. After a certain distance, the repulsive effect of wall disappears.

• **Auxiliary Fields:** This field helps player supporting the striker to attack to the goal more effectively in offence situation. Supporting players is forced to move to clearer areas and critical locations by auxuliary fields. Auxiliary field is an attractive field and makes some points attractor in order to attract supporting players but is not as strong field as ball field. Points given by Equation 3.9 are between two of opponent players and they are specified as an attractor

$$x_{att} = \frac{x_{opp\,i} + x_{opp\,(i+1)}}{2} \tag{3.9}$$

3.4.2 CGF Under Defence Situation

Defence strategy game situation for the home team develops when the opponent player possesses the ball and tries to score. The home team has then the objective to defend its own goal site. Therefore in this strategic game flow two important factors appear: the goal site of the home team and the ball. The ball field is the most important element affecting the result, since defending team first aims to obtain the ball, thus the position of ball being the most critical point. The team also has to prevent the ball from getting closer to the home goal area, this goal area becomes also a critical point. While the wall field, opponent player field, teammate player field and the ball field are modeled with the same potential function as for the offence situation, the goal field is now centered in the home team, thus oppositely situated than for the case of defense.

• **Goal Field :** It tries to take the home team's robots closer to their own goal in order to defend. The direction of the potential field flow is thus toward the home goal site.

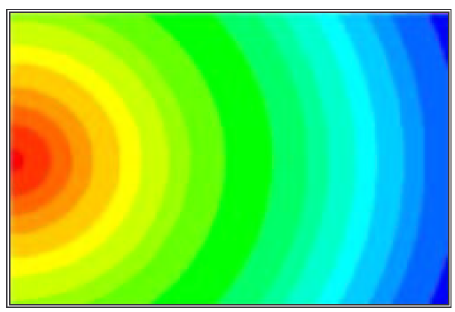


Figure 3.6(a): Potential goal field for defense at 2-D

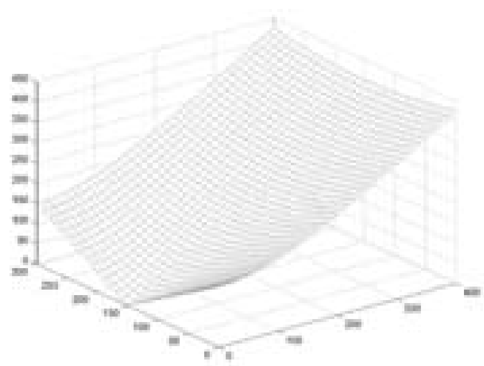


Figure 3.6(b): Potential goal field for defense at 3-D

Figure 3.6(a) shows colored goal field for defence. Here, the direction of the potential field modeled game flow is centered on the home goal. Figure 3.6(b) resembles goal field for offence but valley and peak occur towards the home goal in this case .

• **Auxiliary Field:** In defence situation auxiliary field force players other than players in the most critical region to move some points in order to defend as a whole team by making these points attractors. The magnitude of forces in this field is quite small compared to that of the ball field, but it is useful in affecting the action of the supporting player. Auxiliary points used in defence situation are given by Equation 3.10 and Equation 3.11. In order to create auxiliary field, one of attractive points is placed between the ball and home goal, the other point is placed between opponents and the ball. By means of this field, supporting players tend to be driven critical points nearest to them.

$$x_{att1} = \frac{x_{ball} + x_{goal}}{2} \tag{3.10}$$

$$x_{att2} = \frac{x_{ball} + x_{opp\,i}}{2} \tag{3.11}$$

3.4.3 CGF Under Intercept Situation

The intercept is a situation when neither of the teams possesses the ball. In this case, every players try to catch the ball which is becomes the most important factor for this intercept situation. Once again, the wall field, the ball field, the opponent player field, the teammate player field exist, similarly modeled as in the previous subsections. The goal field does not exist in intercept, since the players merely aim is to intercept the ball. In intercept situation, the ball field has more weights with respect to the other fields due to importance given to the ball as mentioned above.

3.5 Dynamic Role Assignment (DRA)

In order to provide a good team coordination, the distribution of roles over players of team is important. The thesis describes the dynamic role assignment during the game based on potential values of the critical game flow modeled. The strategic situation at which the team is, affects this role assignment. For example, if the team defends, roles related to defence are assigned to players or if the team is intercepting the ball, roles related to intercept situation are distributed to each player. Thus role assignment is done according to the situation indicated by the game flow. Each role are also dedicated to players with certain priorities related to critical regions. The player which is closest to most critical region is assigned the most active role. This priority relation continues to establish orders of importance between critical regions and roles until all roles are distributed. One common role for each situation is used which is that of goalkeeper.

Potential values for each player determine the distribution of roles, since critical regions occur as a result of potential fields built from each strategic region such as goal field, ball field, e.t.c. of a certain situation By considering role priority and ordering potential values for each player, roles are assigned dynamically. When home team offences, role priority is at players which are attacking most effectively, in the same way, on defending role priority is at players which are defending its goal the most effectively. These players are situated on points having the lowest potential value at the field. Other roles are also distributed according to its priorities and its potential values.

3.5.1 DRA For Offence Situation

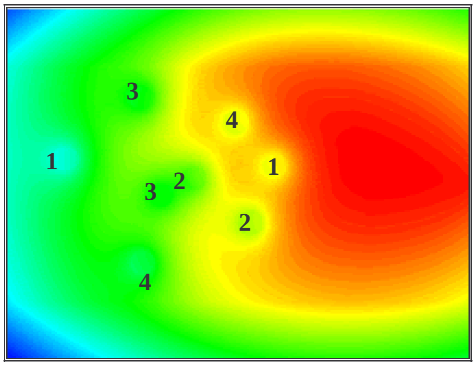
Offence is depicted as a red or reddish critical region with a contour expanding toward the opponent goal. In this critical game region, offencing team has the aim to go to the goal or push the ball into the goal site by following the critical valley in the potential field that extends toward the goal. Therefore, to be near goal is very important. The valleys in the 3-D visualization of the potential field should be generated near the opponent goal by the moves of the home team players. As a result of these details, following roles can be established by ordering based on its priorities:

- Striker: It is a role that has the most priority in this critical zone. Therefore, this role is assigned to player occupying the least of the potential field values. Thus the player strives to be in the potential valley and will try to score pushing the ball towards the opponent goal in this valley of the game flow. If the player does not possess the ball, but is in the critical potential valley towards the goal, the potential values by itself guide the players towards the further depression that the ball creates in the potential field. Therefore the player assigned the role of striker even before possessing the ball will be guided by the game flow to possess the ball and strike.

- Attacker: It has the second priority with the second least potential. It aims to support the striker, this support can be "pass ball to the striker" or "dribble the ball" and can be also "score the goal" if it is at an appropriate position. This support to the most critical role is also strategically critical and is represented by the second lowest discretized level of the potential field.

- Midfielder: This role has the least importance during offencing and the last assignment is done for the midfielder. Potential values of the midfielder is higher than that of the striker and attacker.

- Goalkeeper: It is the nearest player to its goal, since it is defending it. It is assigned to the player depending on its position instead of its potential values.



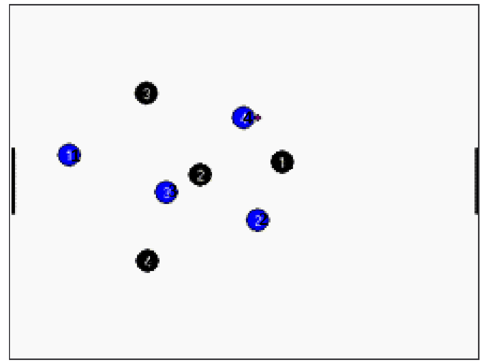


Figure 3.7(a) Example of critical game flow for offence situation

Figure 3.7(b) Example of an offence frame for blue team

Figure 3.7(a) and Figure 3.7(b) illustrates an example where the home team colored blue possesses the ball and attacks the opponent goal. The objective of the home team is to push the ball into the goal. Thus, potential fields of offence critical game flow is as seen in the Figure 3.7(a), the most critical region colored in red become dense around the opponent goal. The blueish areas show the repulsive regions and the attack is thus occurring in the opponent field. The role assignment are:

Table 3.1 Offence Role Assignent Example

Players	Roles	Potential Values
4th player	Striker	1010
3rd player	Midfielder	1350
2nd player	Attacker	1090
1st player	Goalkeeper	1650

From Figure 3.7(a) 4th player is the striker player which is placed in the most reddish region, 2nd player is seen to be in a less reddish region compared to the striker. In Table 3.1 the potential value of the goalkeeper is given but when assigning its roles, its closeness to the its own goal is considered. 3rd player is the farthest in the critical pressure of the opponent goal and is assigned midfielder with the highest potential in its own team.

3.5.2 DRA For Defence Situation

This is due to a critical game flow similar to the attack of the offense situation, where the strategy of the two teams creates the defense situation but now home team having the ball aims at defending its own goal under attack and preventing the opponent to score. Thus here the aim is to generate a role assignment that will elevate the potential values for opponent team around the goal area under attack. In order to elevate a potential value much higher than the lowest that creates a threat, the role of marker is the most important.

- Marker: The role is assigned to player within the game flow of the defence situation with the least potential value among all players in the defending team in the game flow. It presses or marks the player who possesses the ball. It prevents the opponent player to go the goal or shoot. And these attempts are to increase the potential values for the opponent team around the zone from ball to the goal under attack.

- Defender: It is placed to support marker to have the second least potential after marker and has to support him for increasing the opponent potential values in the field under attack.

- Midfielder: It resembles midfielder role in offence. It is assigned to player having the highest potential value with the defending team in the game flow and it has more passive task such as to prevent the opponent player possessing the ball from passing the ball to another player.

- Goalkeeper: It is common role with other situations.

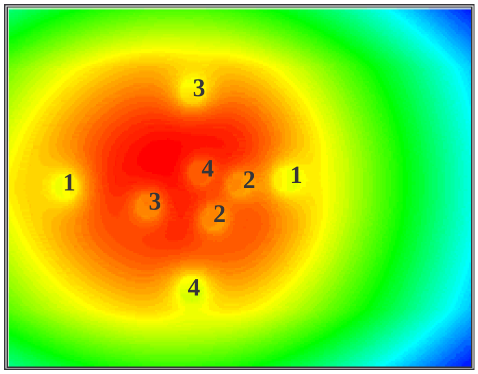


Figure 3.8(a) Example of critical game flow for defence situation

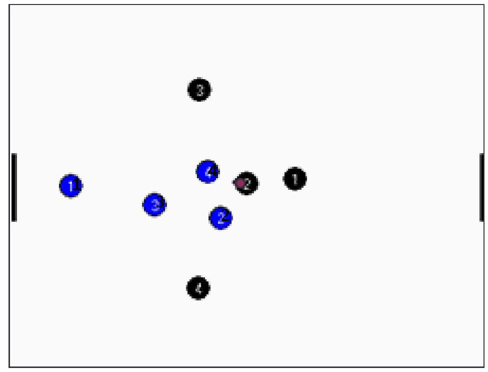


Figure 3.8(b) Example of an defence frame for blue team

In Figure 3.8(a) and Figure 3.8(b), the home team colored blue is defending its own goal. The role assignment for home team resulting from the game flow potential field in the figure is listed below:

Table 3.2 Defence Role Assignent Example

Players	Roles	Potential Values
4th player	Marker	840
3rd player	Defender	920
2nd player	Midfielder	940
1st player	Goalkeeper	1190

Colors of potential help to identify which roles are assigned to which players. 4th player, marker, is in the most critical region represented by red areas in the Figure 3.8(a) and the other teammate being closest to this critical region after the marker is the 3rd player, assigned as defender. There is no importance of potential value for the goalkeeper as described in 3.5.1 section. The midfielder is the player of the

Defending team in order to prevent pass between 2^{nd} and 4^{th} players of the opponent team with the highest potential in its team.

3.5.3 DRA For Intercept Situation

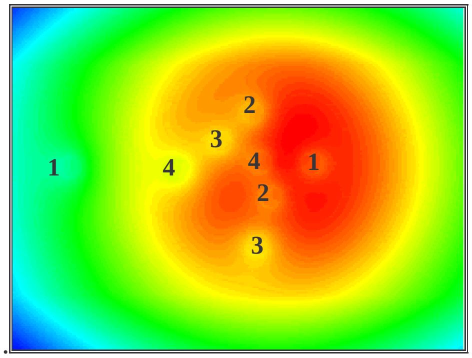
In intercept situation , home team tries to obtain the ball and the game flow occurs in the critical area of the game field where both goal area are under no threat. The ball is the most important object among all objects for intercept situation. The player that is the closest to the ball and therefore the most critical region, has the most probability to intercept the ball. This player has the first priority and called intercepter.

- Intercepter: It is the most privileged role and it is assigned to the player with the least of the potential values among all players. It tries to intercept the ball before the opponent player catches the ball.

- Blocker : It has second and third lowest potential values. These players try to intercept the ball and prevent the nearest player to reach the ball by increasing the potential values of the game flow. After intercepter, it has second priority at role assignment.

- Goalkeeper: It is common role with other situations.

In intercept situations, there are two blockers, intercepter and goalkeeper roles. One of the blockers can be considered as midfielder if desired. This shows that distribution of roles is flexible.



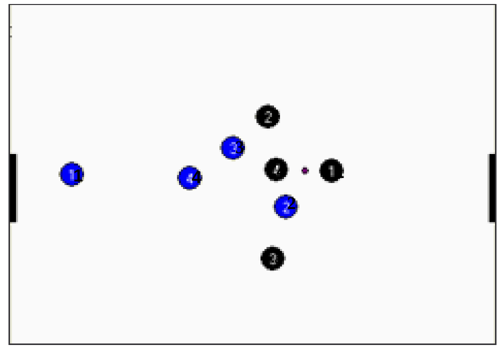


Figure 3.9(a) Example of critical game flow for intercept situation

Figure 3.9(b) Example of an intercept frame for blue team

Fig. 3.9(a) shows the intercepting situation where both teams try to catch the ball The role assignment for this intercept situation for the home team is given at Table 3.3

Table 3.3 Intercept Role Assignent Example

Players	Roles	Potential Values
4th player	Blocker	1110
3rd player	Blocker	960
2nd player	Intercepter	780
1st player	Goalkeeper	1840

It is seen from the Figure 3.9(a) that potential values are lower for the 2^{nd} player meaning that is the closest to the red region and is assigned as intercepter. The other players, assigned as blockers are near in the bluish area.

Although the roles are designed for 4 players, number of players can be increased without effecting the performance. For example, if there are 6 players, in offence, another midfielder and attacker can be added to role list. In defence, roles of another defender and marker, and in intercept another blocker and midfielder can be added. Critical, thus, high priority roles are prefered when adding new roles. Players can switch the its roles dynamically according to current way the play is going, whenever necessary.

3.6 Game Playing Coordination and Role Based Action Selection

In multi-agent games, for instances Robot Soccer, coordinated actions are required to have players sent to positions they will create effective strategy. In this thesis, after roles are distributed to players, roles are mapped to actions, since for each role assigned the players need to make low level coordinated actions such as shoot, pass ball or dribble while avoiding fouls such as running into players. This last item is an obstacle avoidance problem, which in the literature has also been achieved using potential fields. Robots tend to follow the gradient of the potential fields through minimum potential value in order to avoid the obstacles which are formed by opponent player robots and teammate players. Obstacle avoidance is a natural and inherent part of the robot actions in this study which are: move, shoot, pass and dribble.

A player possessing the ball thus around the critical valley of the game flow selects the appropriate action in the game flow according to its potential value and preference of action is arranged in the order of shoot, pass and dribble. In addition, roles of players restrict the actions: The striker shoots and dribbles, the attacker shoots, passes, dribbles and the midfielder passes and dribbles. If the player is in the most critical region, it shoots. If it is near enough the most critical region, firstly it prefers passing the ball to another player placed in the critical game flow valley, if passing action is not suitable, it dribbles to the most critical region. When passing the ball to its teammate, it is searched whether the path of pass action is suitable for doing it. While it is searched if pass action is possible or not, it is determined how the closest repulsive region affects the path of pass action and it is considered possibility that opponent players block the ball. If pass action is impossible, player possessing the ball dribbles until it comes to suitable position for passing or shooting.

Especially, in defence and intercept strategic situations, players does not possess the ball and they make an effort to obtain the ball and immediately score. Thus, in defence and intercept situation, players go to positions by “move” action to elevate the potential value for opponent team and to obtain the ball easily for the home team. In offence situation, players, except the one having the ball, do “move” action to support the player possessing the ball owing to auxiliary fields.

CHAPTER 4

EXPERIMENTAL RESULTS

In this chapter, critical game flow, dynamic role assignment and selection of actions will be demonstrated on robot soccer simulations of an actual game.

4.1 Actual Soccer Game and its Simulation

We have used the FIRA 3D Robot Soccer simulation to test our proposed methodology. We now introduce this simulator program based as a demonstrator. FIRA 3D Robot Soccer simulator is simulator based on two options, either Visual C++ or its programming language, Lingo for multi-robot teams developped by FIRA: Federation of International Robot-soccer Association [37] Programming of strategies are written either in lingo code and placed in a text file or in a C++ DLL that contain the strategies for Blue or Yellow teams. The structure of strategies includes position and orientation of the robots and position of the ball. These parameters are updated and transfered to the each strategies of both teams periodically. The field of simulator is displayed, along with the menu bar and game information in Figure 4.1

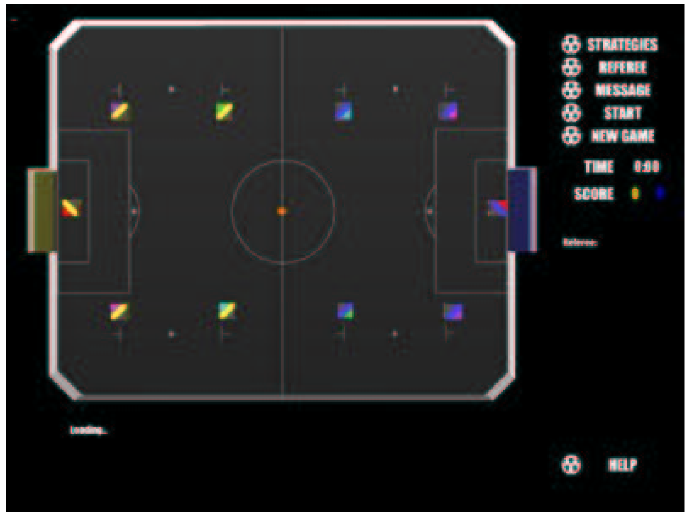


Figure 4.1 Fira 3D Robot Soccer Simulator

FIRA 3D Robot Soccer Simulator contains two teams with 5 players. The players try to score a goal by dribbling the ball only. In testing our system, this constrained capability prevents us of sharing the full specific of our actions that we can display through our simulation and they can only move at two directions as forward or back. Players do not have a kick mechanism and they does not shoot or pass. The simulation resembles that of a hockey game since the ball can not be possessed by a player and just slides away as a player touches it thus rendering. The control of ball is quite hard, therefore players lose the possession of the ball almost all the time.

We have tested our proposed methodology of critical game flow on the blue teams. Players execute various actions based on their assigned roles generated by the criticality levels of a strategic situation, however in the offence situation, a player possessing the ball can only in this simulator dribble to opponent goal. The opponent teams have rule – based team strategies and the opponent team against which we play with our methodology has two attackers and two defenders. The two defenders do not support the attackers but only defend their own goal site. Two attackers cooperate with each other to score. In addition the opponent team does not avoid obstacles, which gives advantages to the opponent team in terms of intercepting the ball. When the blue team loses the possession of the ball, since the positions of blue team players intensify around the critical(reddish) regions, the opponent team tries to score a goal by using the blue/green region outside the critical ones. Once the players approach the ball due to effect of the potential ball field and they obtain the ball. However, if the direction of the players is to the reverse of the opponent goal site, the players should approach the ball by turning around the ball and targeting the direction towards the opponent goal. While a robot is doing this task, the direction of potential field gradients around the ball changes so that robot is guided to move to a point between its own goal and the ball, then it dribbles the ball towards the opponent goal. This last feature is shown in Figure 4.2 on the simulator. In Figure 4.2 blue team attacks the left goal site to score. A player of blue team which is the closest to the ball is at the left side of the ball in the first case and it has to pass to the right side of the ball so that it can attack with the ball towards the opponent goal. At the second case the player passes to the right side of the ball by means of potential field gradients mentioned above. It realizes this task without turning around the ball, since it is able to move at two directions.

Figure 4.2(a) First case for potential field gradients feature

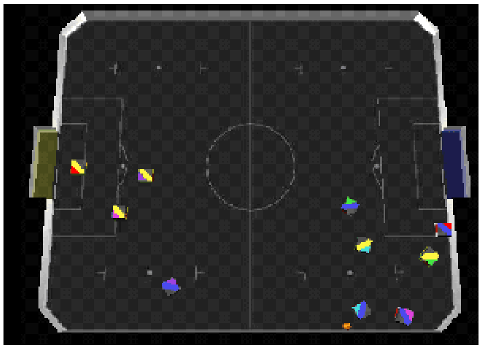


Figure 4.2(b) Second case for potential field gradients feature

4.2 Potential field model of Game Flow levels of criticality

The criticality levels of the game flow in the situation of offence, defence and intercept, will be demonstrated on four consecutive frames at an instant of a robotsoccer game.

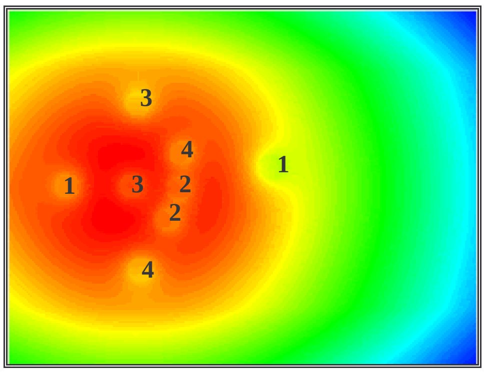


Figure 4.3(a) Potential fields for 1st frame

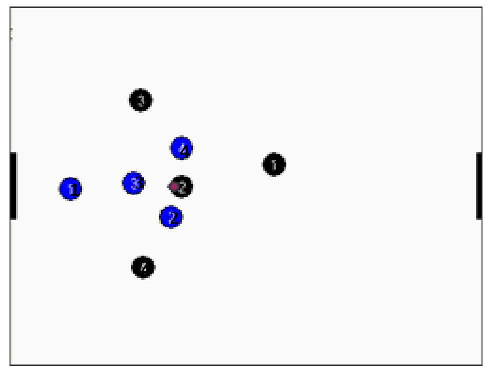


Figure 4.3(b) Team player location on the game field

Figure 4.3(a) shows an instance of the game by its potential fields, taken from a robot soccer game for which the actual game is also described in section 4.1. In Figure 4.3(b) the home team is indicated by blue tokens while opponent is in black. Table 4.1 gives the assignment of roles based on the potential values for each players of the home team(blue token in Figure 4.3b). As seen from the figure, the blue team is under attack and there is a defence situation for home team that has to defend its own goal site and the game flow has a level of high criticality around the ball extending towards the goal area. Since the home team first presses the ball in order to prevent the opponent player from shooting towards the goal site, the high concentration of red (critical region) is around the ball. In this situation, the marker, 3rd player, becomes the most important player that is very near the most critical region and marks the opponent player that possesses the ball by acting to create hills of high potential or green/blue regions for the opponent team by approaching the 2nd player of opponent team which has the ball. The other players do the move action that elevates potential values for opponent team colored as black. Here, the defender places between the ball and opponent player, (4th player) to prevent the pass action and the midfielder, (4th player) also places a position to prevent pass action like the defender, in addition it tries to position a good place in order to attack if the home team possesses the ball. Thus, opponent player is forced to shoot towards the goal as seen next frame, because the failure probability of opponent player’ pass option is high.

Table 4.1 Assigned roles and its potential values for 1st frame

Players	Roles	Potential Values
4th player	Midfielder	900
3rd player	Marker	770
2nd player	Defender	870
1st player	Goalkeeper	910

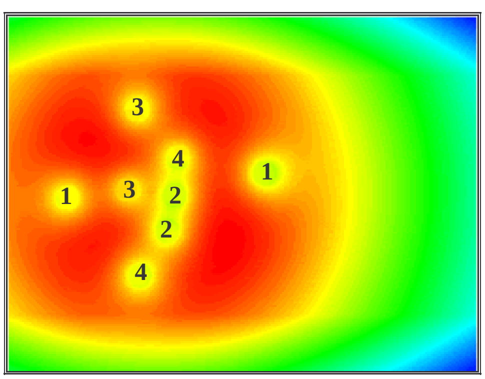


Figure 4.4(a) Potential Fields for 2nd frame

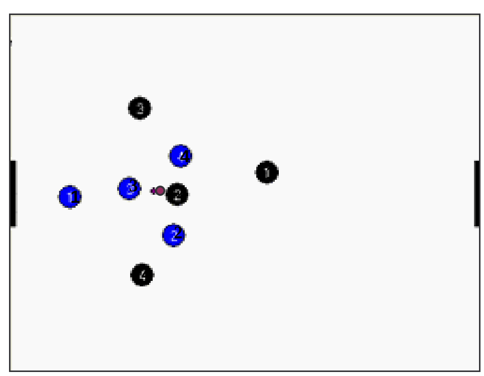


Figure 4.4(b) Players on the game platform

Figure 4.4(a) shows the subsequent 2nd frame of the related game flow in its criticality levels given as potential values. Here the opponent team which is illustrated by black tokens(Figure 4.4(b)) shoots towards the home goal and loses the possession of the ball, and so interception situation occurs because neither of the team players possesses the ball. From Figure 4.4(a) the critical game flow is seen around the ball, with the reddish region. Table 4.2 gives the distribution of roles for this intercept situation. The intercepter role is assigned to 3rd player which is the closest player to the most critical region with its lowest potential value of 600. Intercepter moves into the most critical region around the ball to intercept the ball. The other players do also the “move” action to help the intercepter possess the ball. Here, the one of the blocker, (4th player) tries to prevent opponent player, (3rd player) and the other blocker, (2nd player) does same job as 3rd player. However, the ball moves to the intercepter, (3rd player) and the intercepter is able to the ball easily.

Table 4.2 Assigned roles and its potential values

Players	Roles	Potential Values
4th player	Blocker	640
3rd player	Intercepter	600
2nd player	Blocker	670
1st player	Goalkeeper	640

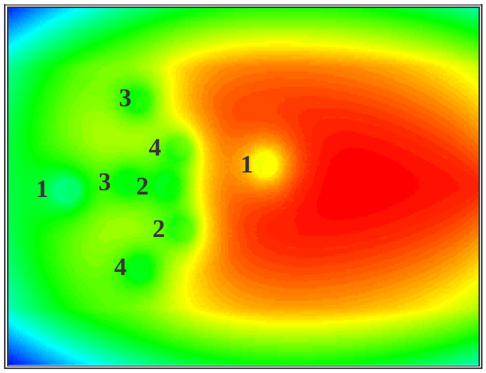


Figure 4.5(a) Potential Fields for 3rd frame

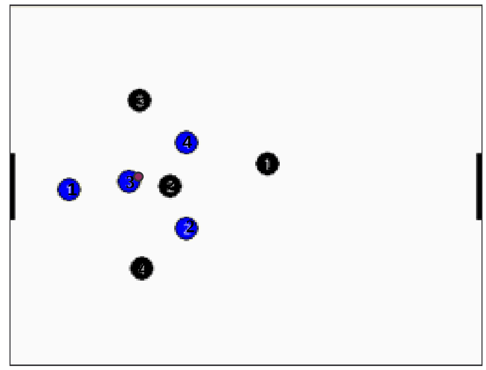


Figure 4.5(b) Players located of the game field

Figure 4.5(a) shows the next frame after interception together with its potential fields distribution. In this frame of the soccer game, the 3rd player intercepts the ball and starts to attack the opponent goal site. Thus, this frame implies the offence situation for the blue home team. This time the reddish region and critical game flow occur towards the opponent goal. The roles assigned according to the offence situation potential values are given in Table 4.3. According Table 4.3, the 3rd player is the midfielder that intercepted the ball in the previous frame, thus possesses the ball. If "pass" action is appropriate, the 3rd player will select the pass option and try to pass to the striker firstly and if not, it will undertake the "dribble" action to carry the ball to a more convenient place to pass it to one of its teammates. The other players, the attacker, (2nd player) and the striker, (4th player) do "move" action and go to the more convenient position in order to receive the ball from the midfielder so that they create the more reddish region near the opponent goal that we see in this particular frame of Figure 4.5(a) and try to score. In this frame, the "pass" option is appropriate and the midfielder passes the ball to the striker so that it is able to push the ball towards the opponent goal.

Table 4.3 Assigned roles and its potential values

Players	Roles	Potential Values
4th player	Striker	1280
3rd player	Midfielder	1350
2nd player	Attacker	1290
1st player	Goalkeeper	1470

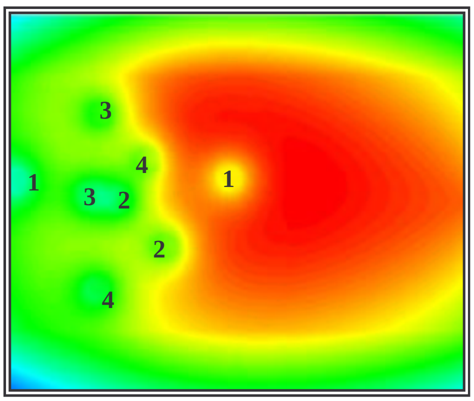


Figure 4.6(a) Potential Fields for 4th frame

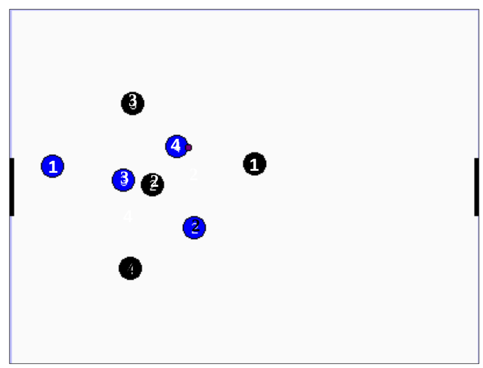


Figure 4.6(b) Players located of the game field

Figure 4.6(b) shows the last frame which the blue team (home team) tries to attack towards the opponent goal. Table 4.4 shows the assigned roles for home team (home team). At this frame the striker possesses the ball and dribbles the ball towards the opponent goal. The attacker supports the striker, so the attacker may change to the striker at the next frames or it removes the attention on the striker by move to opponent goal. Here, the midfielder has no important function to support the striker, since it is far from the critical region.

Table 4.4 Assigned roles and its potential values

Players	Roles	Potential Values
4th player	Striker	1170
3rd player	Midfielder	1300
2nd player	Attacker	1190
1st player	Goalkeeper	1410

These consecutive frames illustrated a home team once in a defensive situation then changed its strategic situation to intercepting the ball, possessing the ball moved into an offensive attack under dynamically changing roles due to these varying strategic situations and role related actions. This section, therefore offers three strategic situations with roles and actions clearly.

CHAPTER 5

PERFORMANCE ANALYSES

5.1 Effects of potential fields parameters on role assignment and coordination

While modeling the critical game flow by using potential fields, parameters used in the potential field function have important effects on assignment of roles and coordination. In this subsection we investigate how the sensitivity of role assignment and positions of robots change according to parameter changes.

This experiment has been done for two parameter sets. Firstly, role assignment and coordination of robots are performed for the first parameter set, then parameters are changed to that of the second parameter set.

First parameter set: k_g=1.25, k_b=3, k_{op}=300

Second parameter set: k_g=2, k_b=3, k_{op}=200

Results have been obtained and three frames are considered as demonstrator of parameter changes affecting role assignments.

Figure 5.1 shows the 18^{th} frame taken from a robot soccer game between two teams where the blue team is the home team to which role assignment are performed based on potential fields. Blue team is in this frame in the defense situation and the roles assigned are given at Table 5.1 When two different set of parameters are applied to the potential fields models of the game flow the potential values at the position of each player vary very little as seen in Figure 5.2 that gives the difference in potential fields for the two parameter sets and no change of roles occur at 18^{th} frame due to potential curve parameter changes. As it is seen from Figure 5.2, the reddish region dominates mostly. Here, reddish region shows there is potential difference of which is the not enough a substantial change to be able to create role changes. In this figure numbers of home team's players are given for the first case. Please note that in Figure 5.1 the positions of players are slightly different, not much. So they are placed on very similar potential curves of the two different game flows occupying almost the same position on the soccer platform. Thus, parameter changes do not affect role assignment and positions of players. The reader wander why the players are at a different location when only the potential curves over mapping the game flow have different parameters. Let us not forget that players are assigned roles that may differ as different potential values occur at their location in the previous frames (this is what we are also analyzing in this subsection). And the actions they take are therefore different in the previous frames yielding different player positions the present frame.

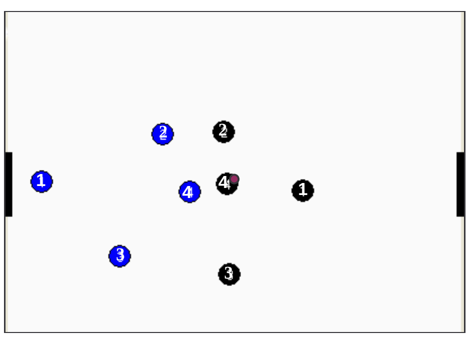


Figure 5.1(a) 18^{th} frame for first case using the first set of parameters with the game flow

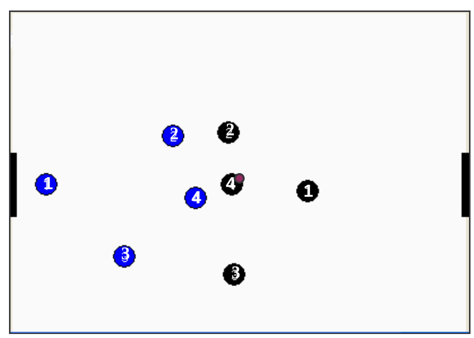


Figure 5.1(b) 18^{th} frame for second case using the second set of parameters with the game flow

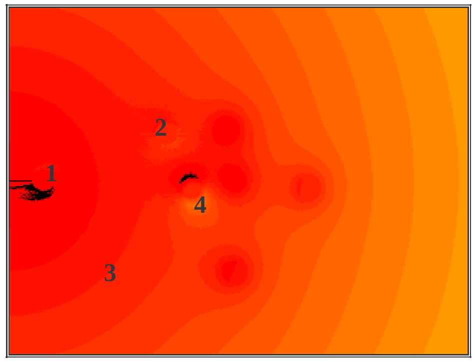


Figure 5.2 Potential fields difference between both cases at 18th frame
Legend: black: potential difference = 0, red: potential difference = small
yellow: potential difference = large

Table 5.1 Roles of players with their potential values for both cases(18th fr.)

18th Frame	First case		Second case	
Players	Role	Pt. value	Role	Pt. value
4th player	Marker	745	Marker	760
3rd player	Midfielder	940	Midfielder	930
2nd player	Defender	820	Defender	820
1st player	Goalkeeper	1020	Goalkeeper	940

Figure 5.3 shows the 75th frame from the same robot soccer game between the same two teams where the blue team acts according to the potential fields values of a defense situation. Table 5.2 gives the role assignments for the blue team players for two sets of parameters. It is seen that the 4th player and the 2nd player exchange their roles after that the game flow is modeled with the second parameter set. Increase of k_g yields the players to come near to their own goal site, the position of the 4th player changes fairly as seen in Figure 5.3. With approaching to its own goal, decrease of k_{op} decreases the effects of the opponent player repulsive field especially for the closest player to the opponent player. These factors cause the

potential value of 4th player to drop below that of the 2nd player. Therefore, the role of the 4th player changes to “defender” such that the 2nd player and the 4th player interchange their roles.

Figure 5.4 shows the corresponding potential field differences at the 75th frame. The orange regions depict more potential difference values than that of red regions, that is, there is more possibility of roles changes in these regions if the potential value change drop of an amount considerable relative to the potential values of the player.

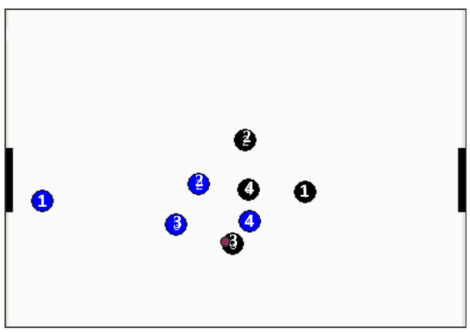


Figure 5.3(a) 75th frame for first case using the first set of parameters with the game flow

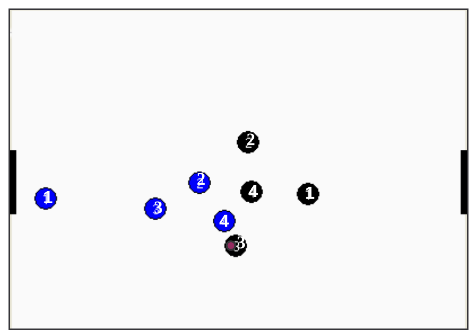


Figure 5.3(b) 75th frame for second case using the second set of parameters with the game flow

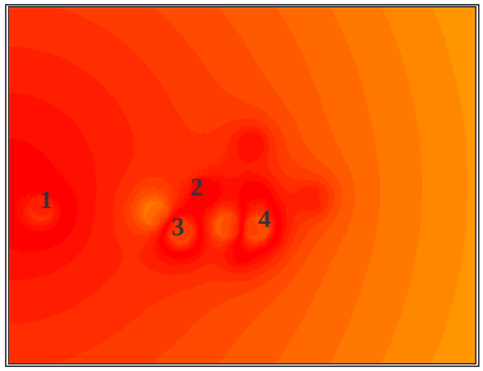


Figure 5.4 Potential fields difference between both cases at 75th frame

Legend: black: potential difference = 0, red: potential difference = small, yellow: potential difference = large

Table 5.2 Roles of players with their potential values for both cases(75th fr.)

75th Frame	First case		Second case	
Players	Role	Pt. value	Role	Pt. value
4th player	Midfielder	920	Defender	830
3rd player	Marker	735	Marker	775
2nd player	Defender	830	Midfielder	850
1st player	Goalkeeper	1015	Goalkeeper	940

Figure 5.5 shows the 89th frame from the same robot soccer game where the blue team is the home team acting according to potential fields methodology. Table 5.3 gives the role assignments for the home team players for the two different set of parameters. It is seen that the roles of all players change except that of the 1st. Since players approach more their own goal site under the increase of k_g, the 4th player are seen to have moved to a more critical location with a considerable drop in its potential value (yellowish dot an Figure 5.6) beyond that of its partners and thus assumes the role of “marker”. The other players have no big differences occurring

on their potential values relative to the 4^{th} player potential values. But, role change of the 4^{th} player causes role change of the other players. Figure 5.6 gives those potential field differences for the 89^{th} frame. Orange regions are possible regions candidate for role changes among those.

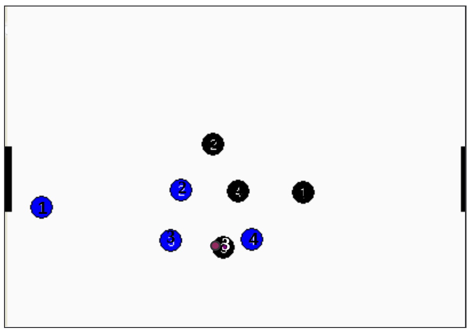


Figure 5.5(a) 89^{th} frame for first case using the first set of parameters with the game flow

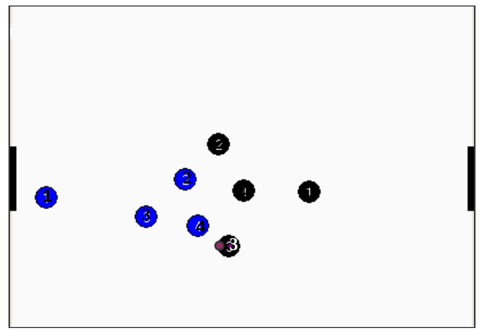


Figure 5.5(b) 89^{th} frame for second case using the second set of parameters with the game flow

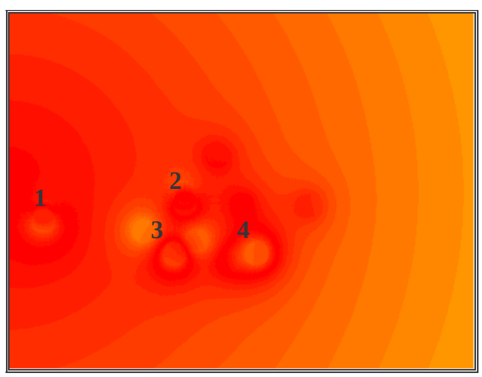


Figure 5.6 Potential fields difference between both cases at 89^{th} frame
Legend: black: potential difference = 0, red: potential difference = small, yellow: potential difference = large

Table 5.3 Roles of players with their potential values for both cases(89th fr.)

Player	Role	Pt. value	Role	Pt. value
4th player	Midfielder	860	Marker	770
3rd player	Marker	760	Defender	775
2nd player	Defender	805	Midfielder	845
1st player	Goalkeeper	1010	Goalkeeper	930

5.2 Action Selection at Offence Strategic Situation

As mentioned in Chapter4, for the offence situation, any player with a given role first selects the “shoot” option; if not possible, it then attempts the “pass” action and at last selects to execute the “dribble” action, in that order. When selecting any action, closeness of that player to the most critical region is a critical issue for action decision making.

As it is seen from Figure 5.7, the attacker, numbered as the 4th player, possesses the ball and has three ordered options in selecting its action: “dribble”, “pass”, “shoot”. The potential value of the attacker is 900 in Table 5.4, in order to shoot to the goal, the potential value of this player should be low enough such that it is well engaged in the critical valley. The range acceptable for the degree of engagement can be determined by a heuristic threshold of how minimum we can allow for striking range at the worst. If the threshold is very low, we may loose the ball ending in an intercept situation. If the threshold is high, the striker shooting the ball may not score. In this thesis work, we selected a linear separation of zones for shooting, passing and dribbling based on the maximum and minimum potential values for the different roles of Table 5.4 In this thesis’ simulations the threshold values are calculated as:

Shoot-threshold value = 0.25*maximum potential value + 0.75*minimum potential value (5.1)

Pass-threshold value = 0.5*maximum potential value + 0.5*minimum potential value (5.2)

This selection reflects that for shooting we require a well defined low potential at the player location. Thus, threshold values for shoot is 815 and threshold value for pass is 1190.In this scene the minimum potential value is 440, while the maximum potential value is 1940. The potential value of location where the attacker stands is higher than the "shoot" threshold value but is lower than the threshold value for "pass". Thus, the attacker selects the pass option and pass the ball to the striker, 2nd player. If threshold value for pass option is selected as 800 that is lower than the potential value of the attacker, the attacker then tries to "dribble" towards the opponent goal site until its potential value is under threshold value, but in our simulation opponent players prevent the attacker to dribble towards the opponent goal and they cause it to dribble towards that player own goal, so that the pass action is found necessary to score by the offencing team.

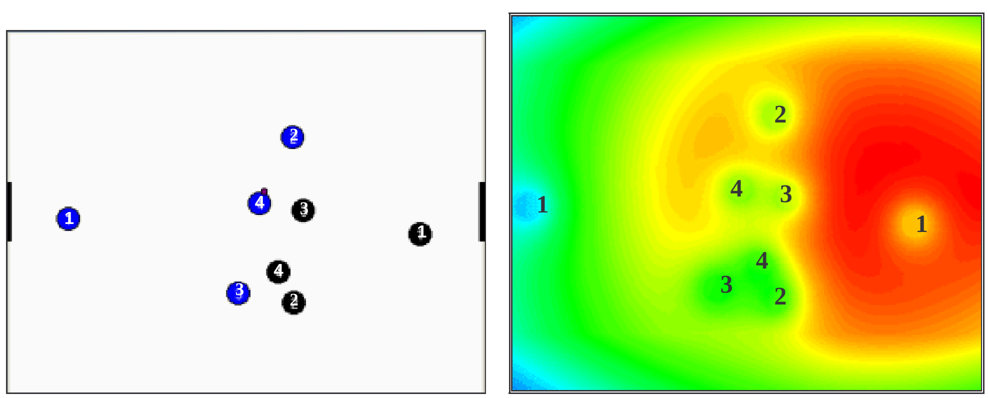


Figure 5.7 The attacker possesses the ball and decides to pass the ball to striker

Table 5.4 Roles of players with potential values for passing case

Player	Role	Pt. value
4th player	Attacker	900
3rd player	Midfielder	1090
2nd player	Striker	860
1st player	Goalkeeper	1480

In Figure 5.8 the striker, (2nd player) possesses the ball and can select the two actions: dribble or shoot. In this scheme the potential value of the striker, 830 is higher than threshold value, found by linear relationship of the maximum potential value(1920) and the minimum potential value(400) which is 780 for shoot. Thus, it selects the dribble action, and It dribbles towards the opponent goal which is the most critical region shown by arrow in Figure 5.8 until its potential value gets lower than the threshold value. If the threshold value for shoot option is selected as 850 that is higher than potential value of the striker, it shoots the ball to the opponent goal immediately. The goalkeeper blocks the ball and the opportunity of scoring is missed.

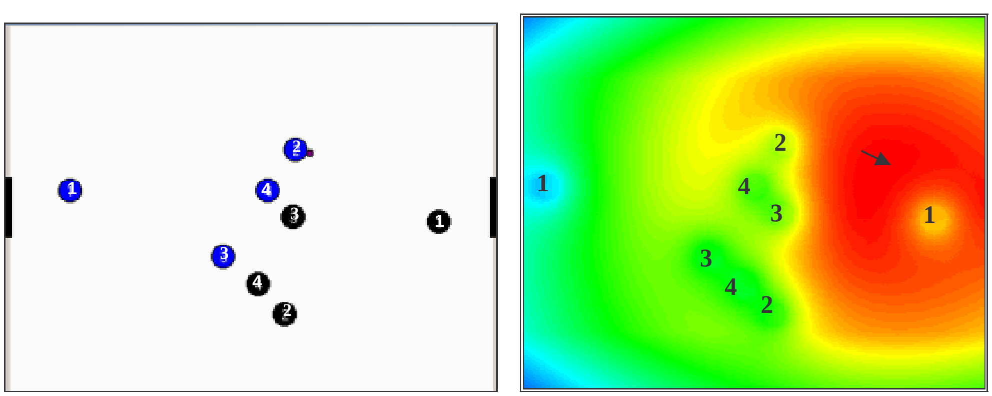


Figure 5.8 The striker possesses the ball and dribbles

Table 5.5 Roles of players with potential values for dribbling case

Players	Role	Pt. value
4th player	Attacker	1010
3rd player	Midfielder	1130
2^{nd} player	Striker	830
1^{st} player	Goalkeeper	1530

In Figure 5.9 which shows a second, the striker, (2^{nd} player) that had decided to dribble from the previous frame until its potential value is lower than the "shoot" threshold value, and gets very close to the most critical region as shown by the arrow in Figure 5.9 and shoots to the opponent goal in this frame, because its potential value is 740 now (Table 5.6) which is lower than the threshold value, while the minimum potential value is 380 and the maximum potential value is 1900. In this portion of the game, the striker succeeds to score.

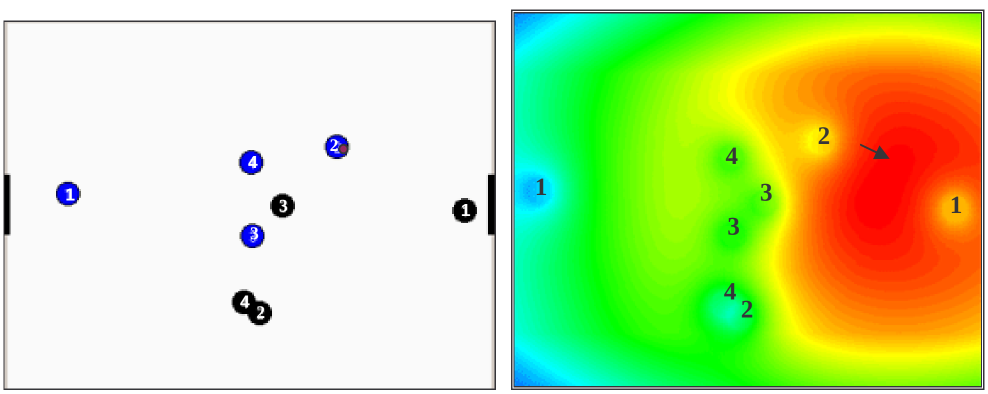


Figure 5.9 The striker positions to shoot the ball to the goal site

Table 5.6 Roles of players with potential values for shooting case

Player	Role	Pt. value
4th player	Attacker	1000
3rd player	Midfielder	1070
2nd player	Striker	720
1st player	Goalkeeper	1550

5.3 Distribution of action types over role assignment

As mentioned again in Chapter 4 robot actions are performed based on their individual roles. Against various opponents, the actions of the robots in the home team are observed, and the influence of a robot's role on its action selection is investigated, especially for two kind of opponents, are which has offensive playing tendency and the other having a defensive strategy. The team having the offensive strategy attacks with more players whereas the team having the defensive strategy attacks with less number of players and defends more in the close vicinity og their own goal site. The following results are obtained for these two kinds of opponents:

Table 5.7 Distribution of roles over actions against the offensive opponent

	Move	Dribble	Pass	Shoot
Striker	%30	%60	-	%10
Attacker	%40	%30	%20	%10
Midfielder	%80	%10	%10	-
Marker	%100	-	-	-
Intercepter	%100	-	-	-

Table 5.8 Distribution of roles over actions against the defensive opponent

	Move	Dribble	Pass	Shoot
Striker	%20	%70	-	%10
Attacker	%65	%20	%10	%5
Midfielder	%90	%5	%5	-
Marker	%100	-	-	-
Intercepter	%100	-	-	-

Table 5.7 and 5.8 show the frame frequency as a percentage of executing a certain type action. From tables "move" is at large the most common action type. In the offence situation the player controlling the ball is frequently the striker (see Table 5.7 and 5.8). It does the dribble action and shoots to score. The attacker is "passing" mostly and also quite often "dribbles", while supporting the striker. As seen from Table 5.7 and Table 5.8 that the attacker takes more responsibility in the offence situation against the offensive opponent. In the same way, the midfielder controls the ball more frequently against the offensive opponent and pass action is used more often since the players are able to get to more suitable position to receive the passing ball and subsequently have more opportunity to efficiently use the received ball.

Results shows that actions that affect the critical game flow are performed mostly by the striker, then by the attacker and less by the midfielder in descending order of criticality. Meanwhile, action types and roles vary greatly according to the strategic capabilities of the opponent.

Table 5.9 Attack measure of offending team against the various team

Opponent	Radius of critical region	Potential values of striker for scoring	Minimum-Maximum potential
Offensive opponent	60 unit	550-650	300-1700
Defensive opponent	40 unit	650-750	350-1900

Table 5.9 gives the scoring measure of the team in the offence situation. Against ones teams carrying the offensive play characteristics the area of critical regions in the game flow is larger than the ones against the defensive ones. Here, it is considered that the radius that the player occupy is 10 unit. Defensive teams try to narrow in every instant of their game the critical regions where the ball lies in. The scoring player which is the striker, has an appropriate very low potential value while shooting and thus in well engaged in the critical region. Thus, the striker has less potential value than those of the defensive teams, since the effect of offensive opponent over the home team is lower.

5.4 Action Performing on Potential Fields

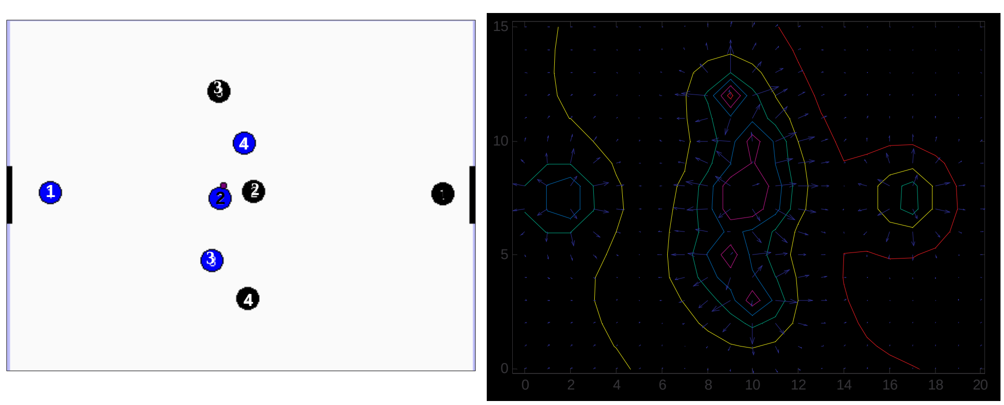


Figure 5.10 Gradients of the game flow for the first robot soccer game frame

In Figure 5.10 the home team (blue team) is in the offence situation. The 2nd player of the home team possesses it and tries to pass the ball to the 4th player which is in a suitable position. In the figure of the right handside vector fields of potential contours given in the left figure are depicted. It is seen that the vector fields are pointing towards the outside of area where the players are. These gradients of the potential field are large around the locations of the players then decrease. The direction of these vector fields is from the players outwards towards the opponent goal site. On the figure we can see that the gradient of potential fields in other words the vector fields increase in intensity in the direction of opponent goal site, around the 4th player. This shows that the 4th player is the player having the most of opportunity to score.

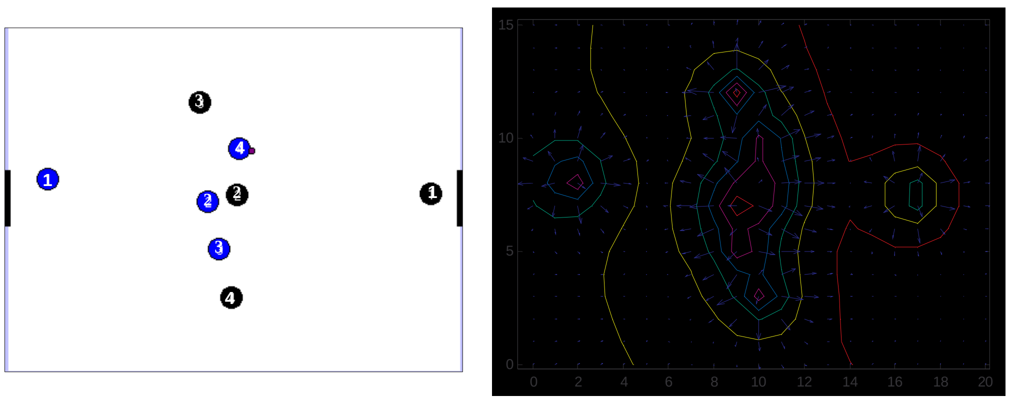


Figure 5.11 Gradients of the game flow for the second robot soccer game frame

In Figure 5.11 the 4th player receives the ball which 2nd player has passed in the previous frame. It tries to bring the ball into area of the opponent goal. The gradient of the potential fields is large around the 4th player and is towards the opponent goal supporting the 4th player action efforts, forcing the 4th player to dribble into the opponent the goal site.

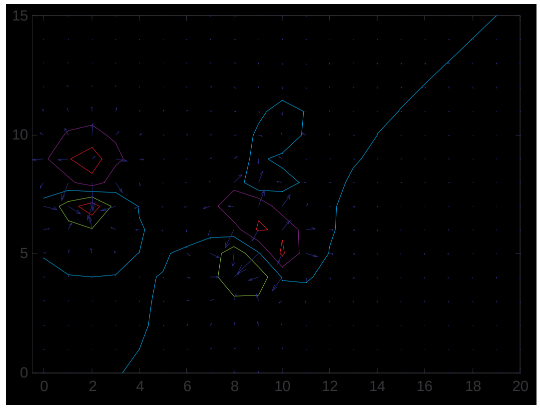


Figure 5.12 Potential fields differences vectors between first and second frame

In Figure 5.12 we compare the two consecutive frames by looking at the differences of their two vector fields. Here, two big differences can be noticed in the vector field changes. One of them is around the position of the goalkeeper and the other is around the 2nd player and the 4th player of the home team. This points to the fact that position of the goalkeeper and the "pass" action of the aforementionned critical players change drastically the gradient of the potential fields by generating the emergence of peaks in these potentially critical regions corresponding to blockage of a direction in the game flow.

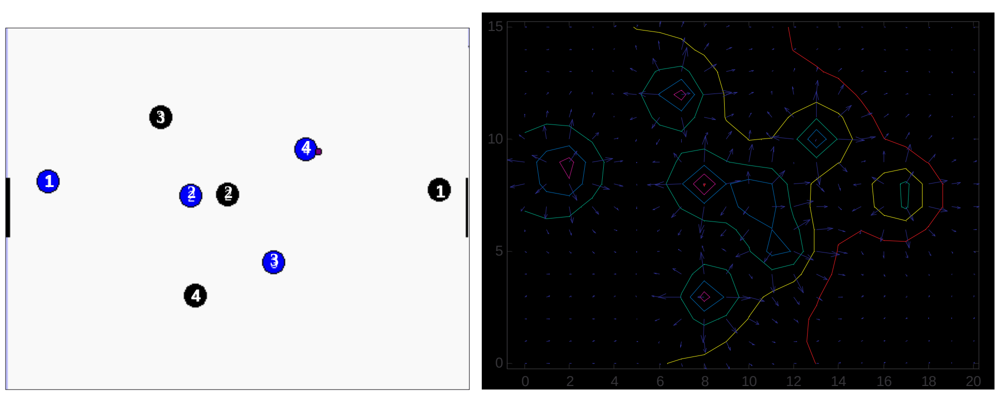


Figure 5.13 Gradients of the game flow for the third robot soccer game frame

In Figure 5.13 the 4th player dribbles towards the opponent goal site until it moves into a position suitable to "shoot". In the figure around the 4th player, the gradients of the potential field is of larger magnitude than that of the previous frame. This forces to the 4th player to shoot to the opponent goal, since acting in the direction of maximum gradient is highly beneficial since this shows that the player is highly engaged in the critical zone and will be able to drastically alter the potential field to the advantage of the player own team. The gradient of the potential fields around the 3rd player of home team is also large and is towards the opponent goal site. It proves that the 3rd player has to do "move" action in order to go in a better location in terms of potential and support the 4th player.

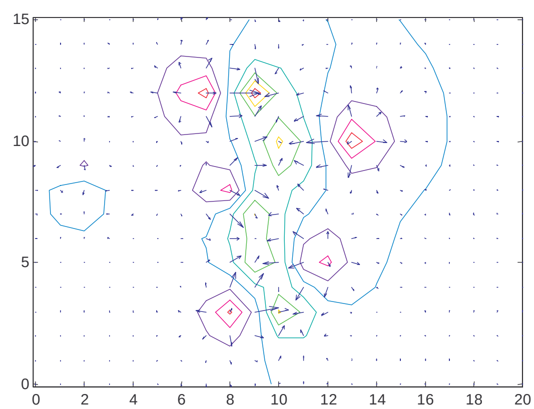


Figure 5.14 Potential fields differences vectors between second and third frame

In Figure 5.14 the vector field differences in different regions of the game flow between the second and third frames are seen. The fact that changes of players' position being yield to increased changes of the gradients of potential field represents the efficiency level in the performance of the play of the corresponding team. These changes of position is seen easily in the figure from the direction magnitudes of the vector fields, such that the vector field differences created by the 4th player dribbling to the opponent goal area and the 3rd player moving are seen in Figure 5.14

5.5 The Effects of the Auxiliary Fields

Auxiliary fields are effective on coordination and action, notably, it helps the players holding supportive roles such as attacker, defender and midfielder, in order to move to the critical points easily. Thus, the team creates stronger strategy at offence and defence situation against the opponent team, furthermore, the functions of supportive players is better enhanced with the use of auxiliary fields. They create more accentuated valleys and peaks yielding to emphasized potential values that the home team and the opponent team can make use of effectively.

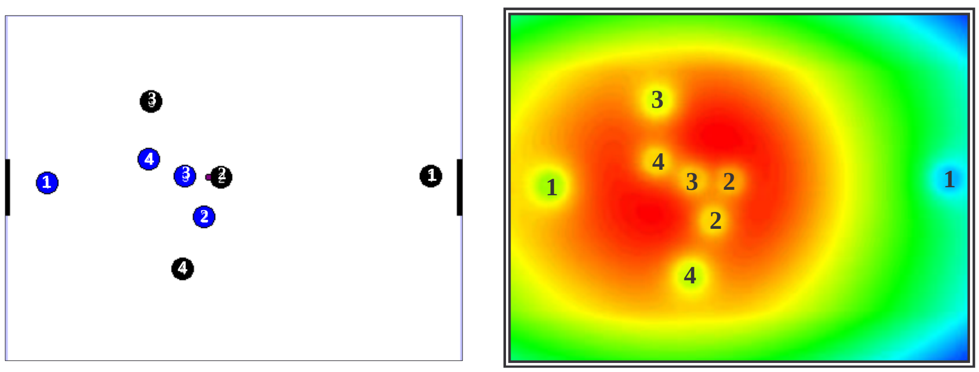


Figure 5.15 Robot soccer game and modeled potential fields without auxiliary fields

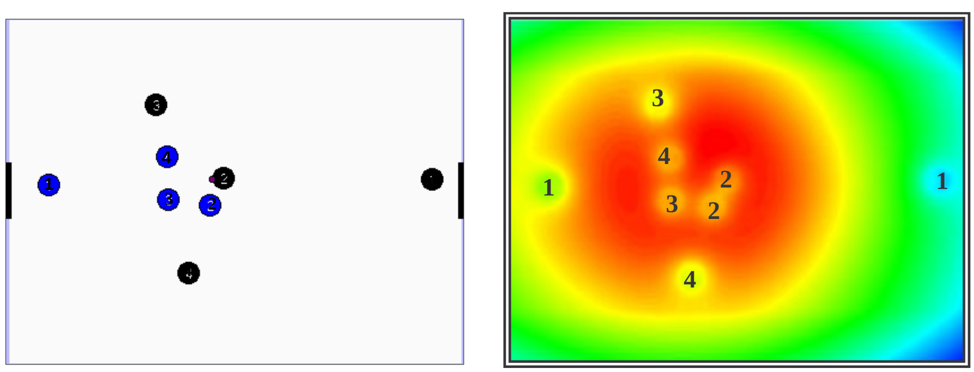


Figure 5.16 Robot soccer game and modeled potential fields with auxiliary fields

Figure 5.15 shows a robot soccer game and potential fields modelled without the use of auxiliary fields. From the figure, it is seen that the home team (blue team) is in the defence situation, and the players position themselves at locations that cut the attack of the opponent team. Figure 5.16 shows the same robot soccer game and potential fields modelled using the auxiliary fields. With the effects of the auxiliary fields, the players are placed at a bit different locations. If we compare these two figures, we see that the home team is able to defend more effectively with the use of auxiliary fields. Especially the 4^{th} player is at a more convenient position that allows him to stop any pass between 2^{nd} and 3^{rd} players of the opponent team. Therefore, all players defend themselves better against the opponent player having the ball (2^{nd} player) better with the presence of the auxiliary fields(Figure 5.16).

CHAPTER 6

CONCLUSIONS

6.1 Conclusions

In this thesis, an approach about robot soccer game strategy by role assignment and action based on the modeling of a dynamical game flow is presented. By using dynamical the game flow model, problems relevant to the role assignment and coordination are solved dynamically in the specific strategic situation of offence, defence, and intercept. Actions of robots are performed to strategically affect the critical game flow by cooling down the potentials (creating higher potentials) of goals under attack or possessing the critical region under intercept. Experimental results presented for the offence, defence and intercepting situations in a simulation demonstrate good and expected performance of our approach under the assumption that the capabilities of each robot is reasonably consistent.

Contributions of this thesis include a new approach on dynamic role assignment and coordinating the actions of a team based on modeling a game flow which is a global model of strategy interplays of two adversary teams. Potential fields have been used for motion-planning [18-38-14-39] or multi–agent coordination recently [16], but now potential fields are able to generate the online changes of a game flow upon which a dynamic role assignment for one of the team can be based thus automatically taking into account the strategic playing pattern of the opponent. Potential fields, determines how well the position of a robot is suitable for the role by analysing the critical zones of the global name played by two teams on the game platform. Actions are generated based on the closeness of a certain player with a certain role to the most critical region of the game is main criteria for selecting the actions.

In this thesis it is seen that a flexible method, so, a single team strategy is designed to play in a global clash of strategies by only the critical game flow model generated by adjusting parameters of the potential field functions, that affect positions of critical points of the game flow, so the team determines its strategy as more defensive or more offensive. Thus it can be created variety plays by regulating parameters against opponent teams having the various strategy from performance analyses.

From simulation results we see that action types and critical regions can change according to characteristic of opponent team such that against the offensive opponents the larger critical zones are created. We also see that the roles and actions have a dense relation with each other according to the generated strategy on the game. Another important result is that players can switch their roles in order to maximize their utility. Furthermore, it is seen from results that the dynamic game flow strategy can be applied to the Robocup competition [40].

6.2 Future Work

There exist some directions for researches in the future. Further improvements can be made in terms of prediction. The position of opponent players and especially the ball can be predicted at previous frame. This prediction enables a planning ability that would make the robot be able to obtain the ball in the game easily when the ball move very fast and the passing between players are done with swift moves. In addition, by predicting the opponent players' moves, the home team may easily block the actions of opponent players by estimating the direction of players' moves.

The parameters of potential fields function is very important in determining the behaviour of the team. Against an opponent team whose game strategy is known, the home team may adjust or change its strategy, but if the opponent team strategy building tendency is unknown, the adjustment of parameters should be made adaptable during the game according to how the game and strategy interplay proceed. Thus, in order to provide adaptation to the game, online-learning can be applied to potential fields function parameters in order to improve performance.

REFERENCES

[1] Michael Bowling and Manuela Veloso. Motion Control in Dynamic Multi-Robot Environments. *Proceedings of the1999 IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA '99), pp. 168 – 173, 1999.*

[2] Tews, A. Adaptive Multi-Robot Coordination for Highly Dynamic Environments. *International Conference on Computational Intelligence for Modeling, Control and Automation CIMCA'2001, Las Vegas, NV, 2001.*

[3] Ball D. and Wyeth G. Multi-Robot Control in Highly Dynamic, Competitive Environments. *RoboCup 2003: Robot Soccer World Cup VI, Springer Verlag, Padua, Italy, 2003.*

[4] Stone P. McAllister D. An architecture for action selection in robotic soccer. *Proceedings of the fifth international conference on Autonomous agents, pp. 316-323, 2001.*

[5] Boon Kiat Quek, Jianxin Xu, and Prahlad Vadakkepat. Developing a Fuzzy Action-Selection Strategy for Mobile Robots. *Proc. of 2nd Int. Conf. on Computational Intelligence, Robotics and Autonomous Systems, Singapore,2003.*

[6] Jong-Hwan Kim, Hynk-sik Shim, Heung-Soo Kim, Myung-Jin Jung, P. Vadakkepat. Micro-robot soccer system: Action selection mechanism and strategies, *Proc. of the 3rd ECPD Int. conference on Advanced Robotics, Intelligent Automation and Active Systems, European Centre for Peace and Development, 1997.*

[7] Frias-Martinez V., Sklar E., Parsons S. Exploring auction mechanism for role assignment in teams of autonomous robots, *Proceedings of the Robocup International Symposium, Lisbon, Portugal, 2004.*

[8] Chaimowicz, L., Campos, M., Kumar, V. Dynamic Role Assignment for Cooperative Robots, ICRA 2002 (ICRA02), Washington, D.C., pp. 293-298, 2002.

[9] Jacky Baltes. Strategy selection, goal generation, and role assignment in a robotic soccer team. *In Proceedings of the Seventh International Conference on Control, Automation, Robotics and Vision (ICARCV), 2002.*

[10] Sony AIBO. AIBOEurope, http://www.**aibo**-europe.com, 16.08.2004

[11] S. Lenser, J. Bruce, and M. Veloso. CMPack: A complete software system for autonomous legged soccer robots. *In Proceedings of the Fifth International Conference on Autonomous Agents, ACM Press, 204-211, 2001.*

[12] B.J. Woltinge. Motion Planner of a Miniature Racing Car. *Master's thesis, University of Twente, 1997.*

[13] Frank Lingelbach. Path Planning for Mobile Manipulation using Probabilistic Cell Decomposition. *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Sendai, Japan, 2004.*

[14] D.-H. Kim and J.-H. Kim. A real-time limit-cycle navigation method for fast mobile robots and its application to robot soccer. *Proceedings of the 2002 FIRA Robot World Congress, pp.17-30, 2002.*

[15] L.E. Kavraki, P. Sventsk, J.C. Latombe, and M.H. Overmars. Probabilistic Roadmaps for path planning in high dimensional configuration spaces. *IEEE Trans. Robot. Autom. pp.566-590, 1996.*

[16] N.M. Amato, and L.K. Dale. Probabilistic Roadmap methods are embarrassingly parallel. *In Proc. IEEE. Int. Conf. Robot. Autom. (ICRA) pp. 688-694, 1999.*

[17] L. Lavraki and J.C. Latombe. Randomized preprocessing of configuration space for fast path planning. *In Proc. IEEE. Int. Conf. Robot. Autom. (ICRA) pp. 2138-2145, 1994.*

[18] O. Khatib. Real-time obstacle avoidance for manipulators and mobile robots. *The International Journal of Robotics Research, Vol. 5, No. 1, Spring 1986.*

[19] Cho, W. and Kwon, D. Sensor-Based Obstacle Avoidance for a Redundant Manipulator using a Velocity Potential Function. *Proceedings of the IEEE International Workshop on Robot and Human Communication, Tsukuba, Japan, pp. 306-310, November 1996.*

[20] Ko, N. Y. and Lee, B. H. Avoidability Measure in Moving Obstacle Avoidance Problem and Its Use for Robot Motion Planning. *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems, Osaka, Japan, , pp. 1296-1303, 1996.*

[21] Borenstein, J., Everett, B., and Feng, L. Navigating Mobile Robots: Systems and Techniques. *A. K. Peters, Ltd., Wellesley, MA, ISBN 1-56881-058-X, 1996.*

[22] J. Borenstein. Real-time Obstacle Avoidance for Fast Mobile Robots. *IEEE Trans. Vol. 19, pp. 1179-1187, 1989.*

[23] M. B. Dias, and A. Stenz. A Market Approach to Multi-robot Coordination. *CMU-RI-TR-0, 2001.*

[24] H. Kose, K. Kaplan, C . Meriçli and H.L. Akın. Genetic algorithms based market-driven multi-agent collaboration in the robot-soccer domain. *FIRA Robot World Congress, Vienna, Austria, 2003.*

[25] M. Spaan. Team play among soccer robots. *Master's thesis Artificial Intelligence University of Amsterdam, 2002.*

[26] M. Spaan, N. Vlassis, and F. C. A. Groen. High level coordination of agents based on multiagent Markov decision processes with roles. *In IROS'02 Workshop on Cooperative Robotics, pp. 66–73, 2002.*

[27] Meyer, J., Adolph, R. Decision-making and Tactical Behavior with Potential Fields. *RoboCup 2002: Robot Soccer World Cup VI. Volume 2752 of Lecture Notes in Artificial Intelligence., Springer, 2003.*

[28] Johannson, S.J., Safiotti, A. Using the Electric Field Approach in the RoboCup Domain. *RoboCup 2001: Robot Soccer World Cup V. Volume 2377 of Lecture Notes in Artificial Intelligence, Springer 2002.*

[29] A. Tews and G. Wyeth. Multi-Robot Coordination in the Robot Soccer Environment. *Proceedings of the Australian Conference on Robotics and Automation (ACRA '99), pp. 90-95, 1999.*

[30] Vail, Veloso. Multi-Robot Dynamic Role Assignment and Coordination Through Shared Potential Fields. *In Proceedings of ICRA'03, IEEE International Conference on Robotics and Automation, pp. 87-98, 2003.*

[31] S. Luke, Hohn C., J. Farris, G. Jackson, and J. Hendler. Co-evolving soccer softbot team coordination with genetic programming. *In RoboCup-97: The first robot world cup soccer games and conferences. Springer- Verlag, Heidelberg, Germany, 1998.*

[32] Zhang, B.-T. and Cho, D.-Y. Evolving Complex Group Behaviors Using Genetic Programming with Fitness Switching. *Artificial Life and Robotics, vol. 4, no. 2, pp. 103-108, 2000.*

[33] Jonatan Aransson. Genetic Programming of Multi-agent System in the RoboCup Domain. *Master's Thesis, Lund Institute of Technology, 2003.*

[34] Kostiadis K . and Hu H. Reinforcement Learning and Co-operation in a Simulated Multi-agent System. *Proceedings IEEE/RSJ International Conference on Intelligent Robots & Systems (IROS 1999), Korea, pp. 990-995, 1999.*

[35] S. Arai, K. Sycara, T. R. Payne. Multi-agent Reinforcement learning for Planning and Scheduling Multiple Goals. *Proceedings of the Fourth International Conference on MultiAgent Systems, pp. 359 – 360, 2000.*

[36] Dudek and Jenkin. Computational Principles of Mobile Robotics. *Cambridge, UK: Cambridge University Press, 2000.*

[37] FIRA, FIRA Official Site, http://www.fira.net/soccer/simurosot/overview.html, December, 2004.

[38] J. Latombe. Robot Motion Planning. *Boston, MA: Kluwer Academic Publishers, Boston, 651 pages, 1991.*

[39] J.H. Kim, K.C. Kim, Y.J. Kim and Prahlad Vadakkepat. Path Planning and Role Selection Mechanism for Soccer Robots. *Proc. of the 1998 IEEE International Conference on Robotics & Automation, pp. 3216-3221, 1998.*

[40] Robocup. Robocup Official Site. http://www.**robocup.org**, *November, 2004.*