A Survey on Strategic Models of Robotic Soccer

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Abstract— Robocup is a competition for robots playing soccer in a simulated field and has been since 1997.This paper is about robotic soccer and various strategies have been focused on. The algorithms surveyed from simple strategies adapted from different domains. The team members, motion, their activities and ball movement is considered for detail analysis. The prominent challenges lay in efficient coordination methods to help win the team. A complete view of the most pertinent coordination techniques proposed that is simulated in soccer field. As learning is a necessity for the behavior to be intelligent the report presents different algorithms that is existing and has been used in robotic soccer.

Key words: robotic soccer, algorithms, agent, Robo Cup, CBR, Ball Localization, SVM

I. Introduction

Development of methods that need to be efficient that has to be interesting to be supported by RoboCup for challenges. Soccer is a game that combines and synchronizes the tasks performed. Quantitative measurement is difficult to achieve team coordination that has to be considered accurate in performance. The main goal is to control the team of players and win matches against the opponent. High level behaviors are used in implementing planning.

Section II mentions the coordination. Section III explains the Case Based Reasoning that is a problem solving method that is similar to human thinking when it comes to solving problems. The CBR integrated with RBR explained how it is used. Section IV discusses about reinforcement learning where there is repeated experimentation that is long term and interaction with the environment. Section V states the random forest method where the values are depended upon each tree by the combination of predictors. Section VI mentions the general decision making that provides a new way in interacting with the agents and the environment by systematically analyzing, designing and implementing in the system. Section VII specifies the Ball localization which focuses on locating the ball using the Convolution Neural Network (CNN) that is better at identifying images. Thus locating the ball position becomes better when using this algorithm. Section VIII marks the lesson that has been learnt from the survey.

II. Coordination testbed

To meet the requirements RoboCup was designed to handle real complexities that fosters Artificial Intelligence by providing challenges in a restricted world. The main focus is of Robotic Soccer for education of students assisting on everyday real life tasks although applications of other domains. Its most practical goal is by developing a team that is completely autonomous robot that a playing soccer to win the opposite team .Even though it cannot be easily achieved by continuous research by bring breakthroughs in the technology.

The RoboCupSoccer has 5 leagues - there is a virtual that is a Simulation League and Small-Size, Medium-Size, Standard Platform and Humanoid leagues. The paper aims on Simulation of RoboCup game that permits virtual game between the teams. The environment-aware body have agents to perform reactive or pro-active actions by individual or group although the interaction is obliged. A set of players is provided by simulator with varied capabilities and the message about this information is received and sent to simulator. The simulation executes in cycles and throughout each step the players perform the required action and by play mode (e.g. one kick per cycle), and that is applied to the player or ball. The next is by simulating the actions performed into the simulator.

III. Case based reasoning

Robocup is a competition for soccer game. Case Based Reasoning is a process that uses previously solved experiences when a new problem is given. Robots aim the ball at the goal to score points.An expert system is needed to control the robots that is the past experiences.

Thus, the CBR and GA was used to quickly retrieve similar cases and for reusing. The combination of CBR-GA helped make better decisions. A hybrid learning was introduced where CBR-GA and RBR is used wherein similar experiences was not found for resusing. Execution of actions that are low level is hard and needs to be efficient and "movement agent" was developed.

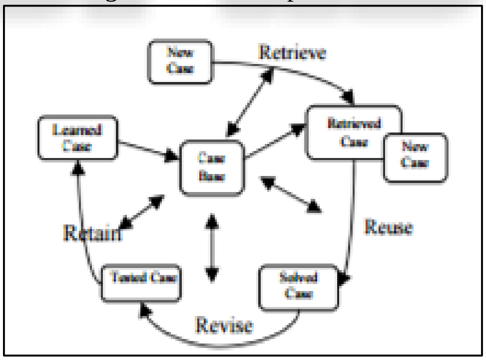


Fig. 1: The CBR Cycle

CBR is the main process and uses representation, indexing and reusing of cases. It is difficult to find a solution with CBR-GA and hence integrating with RBR assists in better problem solving.

$$DIS_{ab} = \sqrt{\sum_{i=1}^{n} w_i \times (f_{ai} - f_{bi})^2} \quad (1)$$

It is the distance formula for the hybrid approach for calculation of the cases. When any case does not match the system uses some basic rules i.e. if it is a match shoots else if it is a match and opposite team player present the pass. In this fitness function is important and its range is from 0 to 1. The case retrieving accuracy is the output of fitness function. The cases presented are not similar sometimes thus it should be changed based on the retrieved cases.

If <State$_1$> & <State$_2$> ... <State$_n$>Then < Solution > With <Weight>

This is the retrieved rule and every rule has weight that matches with the problem given. The experiences helps learn the robots to score.

The CBR system cannot assure that the system performance is good.It has to be integrated to gain a better performance.

IV. Reinforcement Learning

Reinforcement learning helps determine the behavior that is ideal within the specific situation automatically for maximum performance. Complicated decision making is addressed by hierarchical task decomposition strategies.Ball dribbling action is examined to execute layered learning.Dribbling the ball is very difficult to control while moving towards th goal post.Thus layered learning allows to understand such behaviors . There are three identified strategies:

Sequential Learning is a consequential bottom-up approach where bottom layers a frozen after training.

Concurrent Learning learns from succeeding layers by parallely learning from lower layers. Spaciousness increases thus difficulty in learning.

Overlapping Learning seeks to find substitution between the layers and is not needed for the layers to be open during the training.

$[v_x, v_y, v_\theta]'$ is the vector velocity and the subtasks are parallely executed which are ball-turning, target aligning, ball pushing.

$\%S_{\mathrm{Fmax}} = S_{\mathrm{Favg}}/S_{\mathrm{Fmax}}$ it is the maximum forward speed.

$\%\,T_{FS} = t_{FS}/t_{DP}$ it is the time in fault state

$F = 1/2 \cdot [(100 - \%SFmax) + \%TFS]$ is the global fitness

$[\rho_{th}, \gamma_{th}, \varphi_{th}] = [500mm, 15°, 15°]$ the fault state constraint

The convenience in learning and opening of ball pushing is its policy interaction which does not suddenly increase speed of the dribble.

$$r_x = \begin{cases} 1, \rho < \rho_{th} \wedge |\gamma| < \gamma_{th} \wedge |\varphi| < \varphi_{th} \wedge v_x \geq v_{x.max}, \\ -1, \quad \text{otherwise} \end{cases}$$

$$r_y = \begin{cases} 1, & |\gamma| < Ang_{th} \\ -1, & \text{otherwise} \end{cases}$$

$$r_\theta = \begin{cases} 1, & |\gamma| < Ang_{th} \wedge |\varphi| < Ang_{th} \\ -1, & \text{otherwise} \end{cases}$$

$v_{x.max}$, maximum walking speed while walking forward.

The policy expected is the ball should be in possession while walking fast towards the target and it is the function per agent expressed.

It is the evolution of learning with performing the best from each tested scheme and it is separatel measured. However, understanding large numbers requires try-outs in real world problems. Behavior learning is not exactly used, it is grouped or modified to other behaviors. Measuring the results become difficult as positive and negative lines difference is not always clear.

V. Random Forest

The random vector has values that is depended upon each tree and it is tree predictors combination.The splitting of nodes is done by random selection that are reasonably good with noise.Generation of random vectors in ensemble control growth of trees.The voting of popular class is done after generating large number of trees called random forest.

Accuracy characterization of random forest

$$mg(\mathbf{X},Y) = av_k I(h_k(\mathbf{X})=Y) - \max_{j \neq Y} av_k I(h_k(\mathbf{X})=j).$$

the margin function is defined the measure that it is extended to average votes.

As the number of tree increases:

$$P_{\mathbf{X},Y}(P_\Theta(h(\mathbf{X},\Theta)=Y) - \max_{j \neq Y} P_\Theta(h(\mathbf{X},\Theta)=j) < 0)$$

$$mr(\mathbf{X},Y) = P_\Theta(h(\mathbf{X},\Theta)=Y) - \max_{j \neq Y} P_\Theta(h(\mathbf{X},\Theta)=j)$$

the strength and correlation of random forest.

$$PE^* \leq \bar{\rho}(1-s^2)/s^2$$

Generalization error of upper bound though the bound is baggy and these two ingredients of individual classifiers are the strength.

Random forest features has bagging or boosting lesser than chracteristics that are desirable and is parallelized easily.

Bagging helps in enhancing accuracy and gives estimates of error generalization combining ensemble, strength and correlation of trees.It provides higher stability by reducing variance with better performance in data training.

Thus random selection seems to be faster than both adaboost and bagging.

$F^*\log_2(N)/M$ This is the simple analysis that is done.

There is lower correlation that is the indication of better random forest. The more complexity in data sets there is an increase in strength. Only if few features are given as inputs error rates are low.

Once trained, creation of prediction is quite a slack. Training of group of decision trees is very fast. the model becomes slower because the ensembles require more trees.

VI. General Decision Making

A general decision model is defined here for each and every tactic and the decision is based on the goal post's vertical distance and visual angle. An open distributed system is provided with new concepts to analyze and design. Multi agent system (MAS) is a hotspot and has future promising applications which is a special significance theoretically. Here simulation league and there are five algorithms for decision for passing, handling the ball, shooting, player movement, interception.

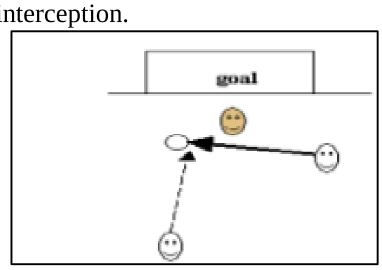


Fig. 2: vertical Pass Inclined arrive

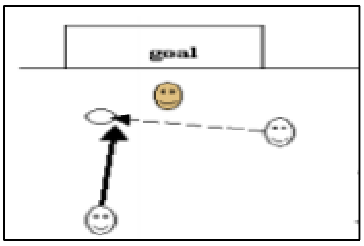
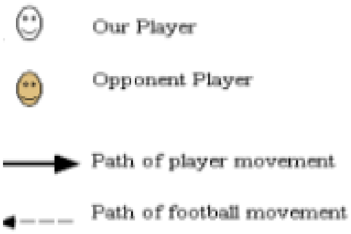


Fig. 3: Incline Pass Vertical



An environment is provided for making decisions and to guide the decision making mature tactics are used.All the tasks i.e the decision making must be made legitimate and the computer executes the commands.

Shooting function for evaluation

$$Shooting\_Success\ (d,\alpha,f,\xi)=\{\frac{1}{(1+d)^2}\cdot\frac{\alpha}{\pi}+\frac{f\cdot\alpha}{f\max(1+d)\cdot\pi}\cdot[1-\frac{1}{(1+d)^2}\cdot\frac{\alpha}{\pi}]\}\cdot\frac{1}{1+\xi}$$

$$\alpha=\arccos\frac{(x1-x)\cdot(x2-x)+(y1-y)\cdot(y2-y)}{\sqrt{(x1-x)^2+(y1-y)^2}\cdot\sqrt{(x2-x)^2+(y2-y)^2}}$$

where,

$$(0,\pi,f,0)\equiv 1$$

the success of shooting is (hypothesis 1)

$$(0,0,f,\xi)\equiv 0$$

(hypothesis2)

hypothesis1: shoot success efficieny where the factors that affects the success in shooting is analysed.

hypothesis2: the basic hypothesis and scoring is based on hypothesis1.

Defensive evaluation:

$$\mathrm{Defensive}(\mathrm{d},\alpha)=\frac{1}{(1+d)^2}\cdot\frac{\alpha}{\pi}$$

according to statistics the formation is better in defense than in offense. The communication must be reliable.

When there is large amount of case in training result might be in efficient. There isn't much knowledge about general decision making and needs improvement.

VII. Ball Localization

In ball localization the most important is that 50% atleast can be any color and the rest as white. The Convolutional neural network is used for ball localization as CNNs has good capability in recognizing images.

Color and edge is used in tracking of the ball since this does not require lots of data to train. CNN has been used and has showed good results and a distribution as output that determines input signla noise.

Activation functions:

traditional activation function as rectified linear units:

$$h(x)=max(0,x)\ .$$

ReLU6 which regularly convergd faster:

$$h(x)=min(max(0,x),6)\ .$$

Soft sign activation that was faster and better providing test results:

$$h(x)=\frac{x}{|x|+1}\ .$$

Models were developed to achieve ball localization and model 1 is created with less neurons to cut the costs of the computation.

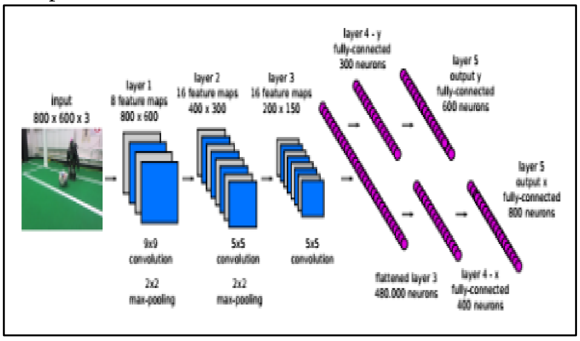


Fig. 4: MODEL 1

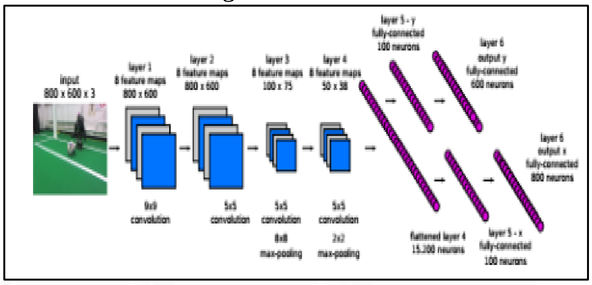


Fig. 5: MODEL 2

training steps has been reduced compared to model 1.

This works on ball prediction only iwth full width and height of the image. Recurrent neural network is used by predicting ball movement and filtering noise. The success is based on measurement of error and knowledge process.

Size of the network is limited due to computer limits comparing low computational robots.

VIII. Hidden Markov Model

Is a classifier defined by using a hyperplane. A model is considered with a play area and a goalie where there is half field view. There are offenders and defenders and a player possessing ball. O1 as a defender nearby to Ob and T1 is a teammate. A set of behaviors is modeled to all the players and goalie.

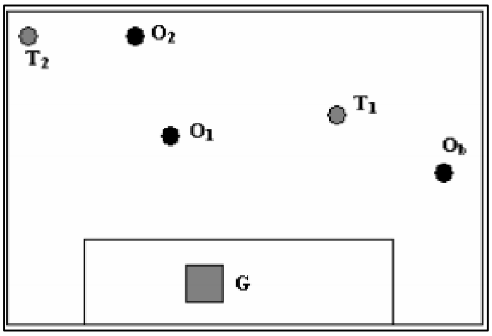


Fig. 6: Half-Field View

A. Behavior Recognition

$\langle o_1, o_2, \ldots, o_t \rangle$ is

$$Pr(S_t = s_i \mid O = o_1, o_2, \ldots, o_t, \lambda) = \alpha_i(t) / \sum_i \alpha_i(t)$$

where α,

$$\alpha_i(t+1) = \sum_j \alpha_j(t)\, a_{ji}\, b_i(o_{t+1})$$

Each behavior is considered and there are states and has fixed life span. The states are Initial, Intermediate, Accept, Reject states and adopted 5 tuples.

It has been in such a way that all the behaviors are distinct and behavior recognizers send the signal uninterrupted. A phase where decision is made and the action of the players is based on that phase.

Action is selected based on the probability at time t for a behavior:

$$Pr(S_t = s_i \mid O = o_{b1}, o_{b2}, \ldots, o_{bt}, \lambda) = \varphi_i(t) / \sum_i \varphi_i(t)$$

where

$$\varphi_i(t+1) = \sum_j \varphi_j(t)\, a_{ji}\, b_i(o_{bt+1})$$

At t=1, the φ_i is given by $\pi_i * b_i(o_{b1})$.

Initial value and observation matrix is a product obtained for first incoming observation. The action performed is immediately done so that there is no delay in executing and the action span continues until next action is reported. This is a phase where is action gets terminated when a new phase has been instructed to be performed.

B. Action Selection Phase

Read behavior from behavior recognition phase.
Update φi(t) for all i at t.
Choose si as act, such that si = Max (Pr (St = si)) in AHMM.
Execute act as goalie action

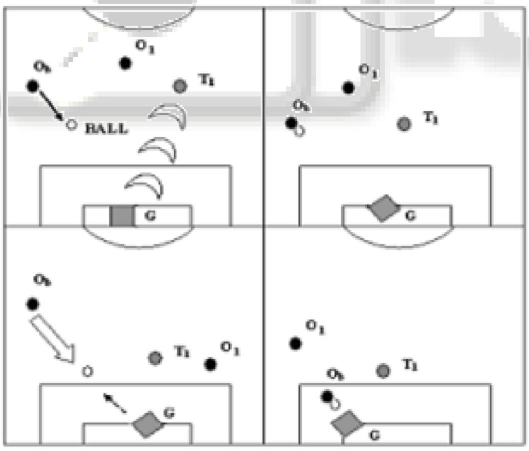


Fig. 7:

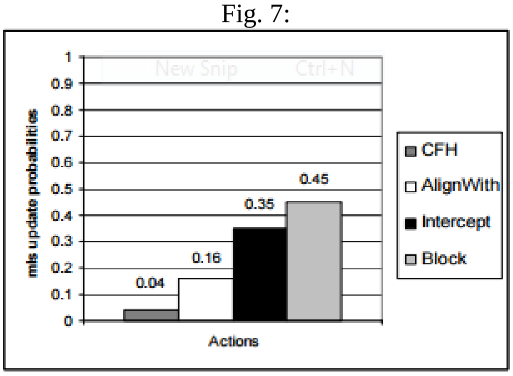


Fig. 8: Bar Graph for Close to Goal area behavior

– Behavior 1: here the ball behavior is taken into account and there is a wide margin while plotting a graph.
– Behavior 2: Here the ball possessed by the player is taken into account.
– Behavior 3: In this the player is close to the goal area, that behavior is when the player arrives near the goal it alarms.
– Behavior 4: Here the shooting of the ball behavior is considered .The player kicks the ball and that behavior is recognized and this is “shoot ball” phase.

Thus the work proposes a decision making HMM and has been used for repetitive behaviors. The algorithm is adaptive and displays various behaviors not based on the order that occurs in the game. Integrating the memory for learning decreases the chances of failures even in unexpected situations.

The algorithm is testes for the game situation to the sequence of behaviors it is been subjected to that results in trials. The RoboSoccer game is a vast set of behaviors where these actions cannot be predicted at the right time.

IX. Conclusion

The work focuses on SVM(Support Vector Machine) where a labeled data is given and the output is optimized based on the algorithm. Based on the comparison made it is found that the combination of Support Vector Machine and Convolution Neural Network together used has high accuracy compared to the others. When Support Vector machine used alone is not very efficient and Convolution neural network leads to over fitting that does not give appropriate result. Thus SVM and CNN gives a better result.

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