Cooperative Robots: Expectation and Message Driven Behavior

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Abstract

Cooperative behavior is a challenging topic for multiple agents systems. This paper presents the results of two different approaches to overcome the obstacles of joint actions: expectation and message driven behavior. A set of experiments has been designed to test the performance of both methods on the behavior of the Robots when collaborating together according to the Sony Four Legged RoboCup Challenge.

1 Preliminaries

The interest in cooperative robots has grown rapidly in the recent years due to its advantages in the solution of complex scenarios, though one of the most challenging topics still remains widely discussed among the field experts. *Collaboration Methods* represent the framework under which the collective behavior takes place and establishes a proportional relation between the robot complexity and the world representation accuracy.

Two clearly identified paths can be taken to confront the robotic cooperation: expectation and message driven behavior. Both approaches are placed in the extremes of the relation between robot complexity and world representation accuracy, therefore the extent to which each method is applied will define the taxonomy of the system.

The *expectation driven behavior* implies that every robot will make decisions according to its perception of the world, and the resultant expectations regarding the situation. As *Cao. et al* [1] describes it (cooperation without communication), the independent collaboration assumes no communication or interaction between the robots and it is the simplest and most limited type of collaboration, where the environment itself is the communication medium.

The *message driven behavior*, on the other hand, relies on the reception of status messages from other robots. Decisions are made according to these messages as they represent individual intentions or decisions.

This paper demostrates the advantages of the message driven behavior versus the expectation method in a *Robot Soccer* environment where an accurate perception of the world has been proved to be essential. A set of experiments has been designed to test the performance of the *overall behavior* when confronted with complex tasks in a constrained environment.

It is essential to understand the complexity of cooperation in a constrained environment. Each robot must be able to percept the world around it and interpret the meaning of such perception in order to be able to interact with its environment. For this particular robot soccer scenario, limitations such as lighting conditions or computation power and speed makes the perception and interpretation of the world a very difficult task.

The data collected in the experiments will measure the *confusion level* between the robots, that is, the proportion of times that the robots make a decision interfering with the collective behavior.

$$confusion = \frac{numberOfDecisionsAgainstCollectiveBehavior}{totalNumberOfDecisions} \tag{1}$$

1.1 Related Work

1.1.1 Collaborative Behavior

Collaborative behavior has been described in many ways (*Cao. et. al.* [1]), mainly according to the objective or the process under which the behavior takes place. It has been used in applications where either the problem is too complex to be solved by one robot, or the complexity of the environment requires a single too complex robot. Some of the well-known scenarios where multi-agent systems have been used are:

- unknown environment mapping [2]
- small block pushing and object manipulation [3] [4] [5] [6]
- foraging (typically toxic waste cleanup and rescue) [7] [8] [9] [10]
- route planning [11] [12]

These scenarios are in certain way related to robot soccer. When playing soccer with robots, despite the fact that the field is known and stable, the robots will move, making the environment around the robot change rapidly. One of the essential tasks when playing robot soccer is ball handling and pushing (or kicking), so small objects manipulation is also involved. Route planning is also related in terms of goal oriented routes with obstacle (namely other robots and referee) avoidance. Foraging might be the most related area to robot soccer in the sense that several robots must accomplish the common task of finding the ball "hidden" in the environment, and placing it in the opponents goal.

Despite all the applications are problem specific, they share the common topics of social organization and *Collaboration Methods*

1.1.2 Robot Soccer Teamwork

One of the most extended applications of multiple robot systems in the last few years is *RobotSoccer*, where homogeneous robots must compete with each other in a soccer game. This particular scenario reflects the challenge of the collaborative behavior method due to the combination of computing limitations in the robots and the complexity of the world representation. It is particularly obvious the need of a good choice in the selection of the extent of either approach (expectation and message based).

Dynamic role assignment [14], *observations sharing* and *learning methods* [15] are some of the ideas that have been already used in robotic soccer [17].

As part of the yearly improvement in the RobotSoccer game, old rules are eliminated to let new less restrictive rules be part of the game and improve the team performance. One of the focus issues for the 2006 RoboCup Challenge is team work, where robots must play with the ball showing a collective behavior. For this reason, this Challenge environment suits our needs perfectly to test the *Collaboration Methods* and measure the behavior change in the team according to a particular constraint.

2 Methods

Both *Collaboration Methods* have been implemented in order to prove the advantages of using the *messages driven behavior* method versus the *expectation driven behavior* method.

We defined a constrained environment to be able to test this methods. The ball representation has been chosen to be the parameter to be considered in our experiments. The reason to choose this particular parameter relies on the fact that the representation of the ball (namely ball speed, position and direction of the movement as the robot "understands" them) is directly related to the *confusion level* due to its relevance in the conditions under which the decision are made (when the robot decides to grab the ball).

As for the general scenario, the tests were carried out using three robots passing the ball to each other. Different *experiment constraints* were considered and introduced to reduce the possible noise of the system:

- Environment independence. The experiments were done within the soccer field using three different passing/blocking angles to discard the influence of the environment (lighting, shadows, background, etc).
- Ball pass independence. This will assure that the ball hits the robot's chest with a constant speed, direction and rotational speed. The distance to the ball will also remain fixed.
- Self positioning independence. Robots will be placed at a steady position with a fixed distance between them.

Experiments were done by eliminating those constraints in an orderly fashion to get a clear idea of their individual relevance in the general behavior.

The last and final test consisted of letting the robots play the ball with no human intervention in order to observe the overall behavior (autonomous play capabilities). This test will also be usefull to measure the emergent behavior and the possible applications of the *message driven behavior* in a real robot soccer game.

Several prior tests and improvements were done in order to develop a stable system to test the collaboration approaches. Issues such as kick selection, ball grabbing, teammate localisation and self-positioning [18] [19] proved to be an essential matter in order to accomplish meaningful results in the behavior performance measurement.

Before performing these experiments, the *accuracy levels* of the robotic pass task has been measured and the results are presented here:

- Passing the ball to a teammate. The success rate is conditioned by the position of the ball (steady position under the chest) and the presence of a non moving teammate - 50% (% of success)

- Blocking the ball when receiving a pass. The success rate is conditioned by the direction and speed of the ball (steady parameters in the test) and optimal visibility conditions (no objects interfering the view of the field) - 60% (% of success)

- Ball representation. The accuracy is conditioned by a steady robot and ball positions, and optimal visibility - 90% (% accuracy)

2.1 World Representation

In order to be able to play the ball, the robots must be at least capable of localising relatively both the ball and at least one of their teammates to perform a pass. This is indeed not a trivial problem due to the fact that both self and ball localisation rely on vision (image processing) which is a complex topic (object segmentation, light invariance, color spaces, etc).

We chose the *ball status* as our testing parameter due to its important role in a passing game. Namely, the ball status can only be *taken* and *non taken* (see figure 1) . The taken status reflects the fact that the ball should not be taken by any robot (except the robot that has the ball), while the non taken status, reflects the possibility to grab the ball for all the robots.

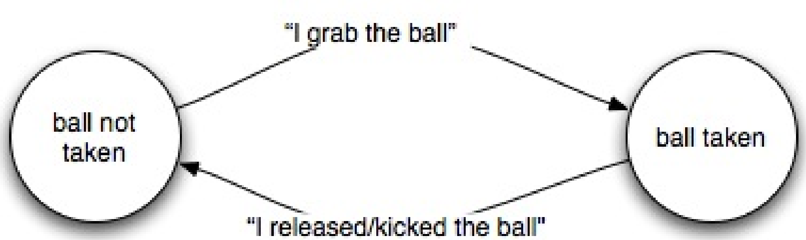

Figure 1: ball status and decision messages

Both *Collaboration Methods* have been modeled and implemented according to this parameter selection. This modeling process is reflected in the conditions under which the decisions are made.

For the case of the *expectation driven behavior*, each robot will cooperate without communication (independent collaboration) according to its perception of the world and the decisions will be taken based to its expectations regarding the ball status. This is clearly affected by the way the robot "understands" the world (particularly ball position and speed).

On the other hand, substituting the expectation by a *message driven behavior*, the robots will behave according to the messages received from their teammates, regarding to the ball status, and their own perception of the world. This implies that every robot will be responsible for communicating its teammates when it made the decision to grab or release the ball and not to grab the ball if a teammate message stating this intention has been received (*extremely simple status messages*). This responsibility models a social rule in which the "robot in posession of the ball" role should only be taken by one robot at a time.

It is important to note that the *message driven behavior* method does not rely on any communication synchronization mechanism nor message arrival guarantee, therefore the robots will still be able to decide to get the ball at the same time.

The selection of the *ball status* as our testing parameter simplifies the messages framework (no need to send complex messages containing measurements, observations, etc) and will highlight the benefits of these *extremely simple status messages* due to its relation with the ball representation, which offers an already measured accuracy.

This setup allows us to observe the *confusion level* in the overall behavior.

Intuitively we will expect the first method to be sufficient for a very accurate world perception, but according to the *accuracy levels* provided by the platform we can expect the *message driven behavior* to reduce the *confusion level* and therefore improve the overall performance.

2.2 Behavior Constraints

As part of the prior work to perform the experiments, some stable implementation had to be accomplished which will represent the behavior constraints under which the confusion was tested.

These are the behaviors [19] implemented at the time of the experiments:

- Block the ball when its in range or its speed and direction indicates that a pass has been performed and the robot is the target.

- Approach and grab the ball and make sure it is under the robot's head.
- Find the closest partner (in angular terms) and turn around the ball to kick.
- Kick the ball only when it surely is in front of the robot's chest.
- Always look at the ball and turn the body towards the ball.

As can be appreciated, the behaviors do not model completely the game and are independent of the number of robots, but represent a general guideline of behavior composed by simple more basic behaviors. In this sense, the decision framework models a layered environment where complex decisions rely on the completion of simple decisions and consequent behaviors.

3 Results and Discussion

As passing the ball represents an accuracy constraint, two different experiments have been carried out. In the first one, human intervention will be used to throw the ball towards the robot, while in the second one a robot will be used for this task.

All the experiments were performed in an official soccer field according to the regulations of the *Robocup 2006* [16].

Its important to note that the experiments were performed under the influence of the already mentioned *experiment constraints* and conditioned by the *accuracy levels* previously measured.

These experiments allows us to establish a relation between the error rate associated with the considered parameter (the *ball status* - ball representation) and the performance improvement (*confusion level*).

The last set of experiments were performed in a *free play* mode where the three robots were allowed to play and pass the ball to each other with the singular restriction of an enclosed area and only peforming human intervention to keep the robots within space limits. This test proved to be a very successful tool to observe *emergent* behavior not explicitely programmed.

3.1 Human-Robot ball play

This experiment was designed to test the confusion level present in the collective behavior in a very restrictive scenario where the ball is passed by a human towards one of the two robots alternatively. Both robots were placed 53 cm apart and facing the ball, located 70 cm away.

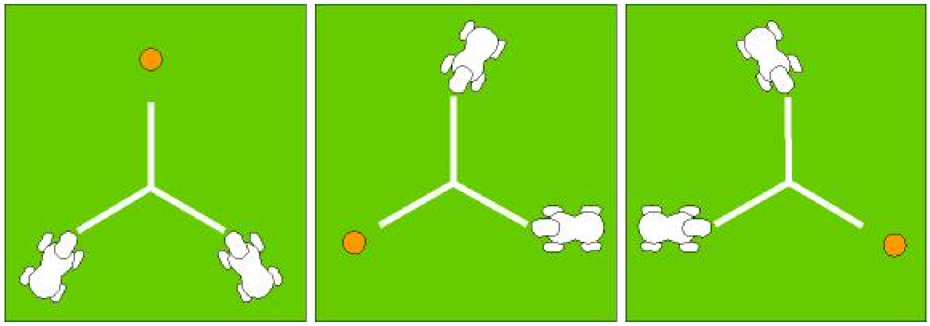

Figure 2: Experimental setup

The experiment was run three times per *Collaboration Method* changing the shooting and robot positions according to the three possible angles (three vertices of a triangle). At every angular location, ten passes were performed. The selection of this setup reflects the *experiment constraints* mentioned above and will ensure independency from conditional factors. As no change was present in the three runs in terms of *confusion level*, we can conclude that the environment was not interfering with the results (lighting conditions, background, etc).

3.1.1 Expectation driven behavior

In such a scenario, the results showed an average confusion level of 46 % with a standard deviation of 5.7 %. This means that about 46 % of the game time will be affected by confusion (more than one robot will try to grab the ball at the same time).

Despite the fact that the robots were placed at enough distance to avoid collision (but not necesarily confusion), the ball perception was clearly holding back the performance because the confusion was an effect of a not enought accurate *ball representation* and therefore a wrong *ball status* perception.

3.1.2 Message driven behavior

When using the ball status messages, the confusion level dramatically dropped to a mere 3.3 % with the same 5.7 % standard deviation.

This result represents a clear proof of the advantages of using *extremely simple status messages* even when the message topic is related to a high accuracy parameter (90% accuracy in ball representation).

It is interesting though to observe that this result is not trivial due to the lack of message synchronization processes and reliable message transport protocols.

3.2 Robot-Robot ball play

Following the same line of the previous test (same scenario, distances and number of runs), we performed an experiment where the ball was passed by a third robot to eliminate any human intervention.

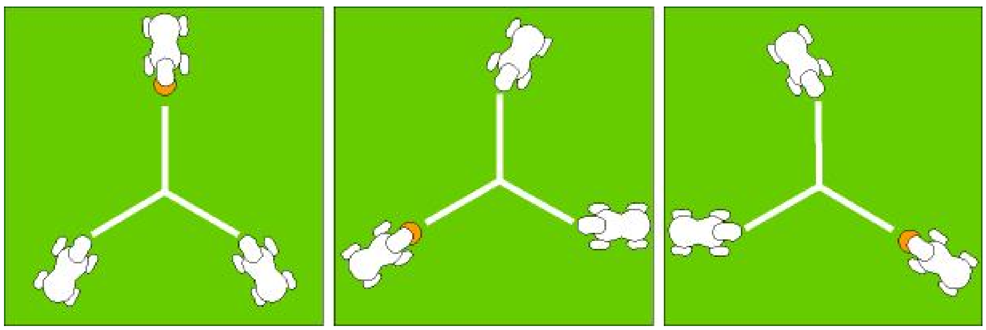

Figure 3: Experimental setup

This is particularly interesting to observe the effects of the human pass in the overall behavior.

3.2.1 Expectation driven behavior

Surprisingly, the performance for the robotic pass improved, reducing the confusion level to 33 % with the same 5.7 % standard deviation.

Such a result shows that despite the fact that the robotic pass is less accurate than the human pass in terms of direction, it is performed in optimal conditions for the robot collaboration (strength, rotation, speed, etc).

This will only benefit the final test, free play, where the robots play with no human intervention.

3.2.2 Message driven behavior

For the case of the message driven test, the performance also rised to the same level as the human pass message driven test, dropping the confusion level to the previously seen 3.3 % and again with the same 5.7 % deviation

Experiment	confusion level	deviation
human-robot expectation based	46 %	5.7 %
human-robot messages based	3.3 %	5.7 %
robot-robot expectaion based	33 %	5.7 %
robot-robot messages based	3.3 %	5.7 %

Table 1: Results summary

3.3 Free play

For the case of the free play experiment, some additional behaviors [19] were introduced, namely keep a certain distance to the ball when it is in possession, and wait ten seconds when the ball is not in possession before the closest robot decides to grab the ball.

This additional information proved to be extremely efficient in an autonomous ball game, when the three robots keep playing the ball regardless the environment, beeing human intervention needed only to keep the game within field range.

The fact that no human intervention is needed becomes evident when the test is performed and the robots are capable of playing continuosly and autonomously as long as they can see the ball.

This test was performed using the *message driven behavior* method. The reason to use only this method is the willing to test the feasibility of such *Collaboration Method* in a real robot soccer game.

In terms of performance, the robots were able to play the ball continuously with the single particularity of having to keep the ball inside the field (a mere 5% of the total game play).

4 Future Work

Due the continuous line that links the expectation driven method with the message driven method (there is an infinite number of degrees of extent to implement a *Collaboration Framework* using both methods together), its evidently needed to define status points in this line in order to be able to measure the improvement in the overall system behavior under particular circumstances. These status points will represent associations between perception parameters and status parameters (as we did with ball representation and ball status).

This belief will guide our future work towards an optimal collaboration framework where decisions can be made according to the world representations complexity vs. message computational cost.

Reinforcement Learning could also be applied to let the robots learn what messages to send given a particular situation, when to send them and what effect do they have in the overall performance.

5 Conclusions

After the completion of the experiments and the analisys of the data, we can conclude that simple messages related with not enough accurate perceptions (such as the case of the *ball status* and *ball representation*), that are otherwise essential for the *expectation driven behavior* method, can greatly improve the overall behavior performance and do not require a complex messaging framework.

We have shown that a simple message regarding the status of the ball will reduce the confusion in the collective behavior in more than 40% and will increase the importance of the emergent behavior for this particular task. One of this clearly emergent behaviors is the fact that, on average, the robots tend to keep a perfect triangle when playing in free mode. This behavior can be explained by the size of the robots combined with the "keep a steady distance to the ball" behavior, facts that makes them avoid a long period "too narrow" or "too wide" triangular formation.

This shows that a well designed *Collaboration Framework* (the right mixture of *expectation* and *messages*) offers more benefits in the overall behavior performance than the naive detailed model of the game, where all the cooperation is solely based on *expectation*.

In terms of the applicability of our work in a real robot soccer environment, we can say that the *message driven behavior* method could be used to improve the team performance. One of the areas less exploited so far in robotic soccer is *team strategy*, which is directly related with cooperative behavior. In this relation, *team strategy* will benefit from the advances in cooperative behavior due to its relevance in the *overall behavior* performance improvement as we showed with the experiments. The *message driven behavior* method as we have described and implemented it, models a simple passing game with a collective behavior ("play the ball"). The same approach can be used to model different collective behaviors such as "move the ball towards the player closest to the opponents goal", "keep the ball in the opponents field" or "avoid goals for the rest of the period" to mention some of them.

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