A Description of the rUNSWift 2003 Legged Robot Soccer Team

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Abstract. This paper describes the 2003 world champion legged robot soccer team, rUNSWift. The 2003 rUNSWift team is enhanced in a number of ways over previous teams; both long and short range collaboration between team members was carefully crafted, a new method of ball localization was used when the ball was close, new tools were developed for developing filters for objects returned by the vision code, self-localization was simplified, opponent localization was significantly improved with distributed data fusion, ball tracking was improved to account for the ball's velocity, edges and lines on the field were used to assist in self-localization, and automatic gait optimization was used to improve the forward walking speed of the robots. The result of these changes is a team that is significantly improved over previous teams.

1 Introduction

This paper describes the rUNSWift 2003 legged robot soccer team. This team was based upon the rUNSWift 2002 team [1], with significant extensions. In particular, the architecture of the code was changed from a single monolithic object in the operating system into a number of interacting modules. At the same time, many of those modules were enhanced. As a result of these changes, rUNSWift was the world champion team in the legged league of the RoboCup 2003 international robotic soccer competition.

Due to space limitations, not all the details of the technologies developed are described in this paper. Readers are referred to the undergraduate theses of the student members of the team, which will be released as UNSW technical reports in late 2003, for complete details (also see [**?**]).

This paper describes a number of distinct changes to the rUNSWift team. In Section 2 we describe the organisational changes to the codebase itself. In Sections 3 and 4 we describe the team coordination used. Vision changes are described in Section 5 before moving to object tracking and data fusion in Section 6. Section 7 gives an overview of the automatic gait optimisation, and finally, Section 8 describes the code used in the three technical challenges.

2 Internal Breakdown

The rUNSWift 2002 legged robot soccer team [1] used a single operating system (OS) object. In contrast, the 2003 team has broken this into multiple OS objects in a similar manner to [3]. There are now three OS objects; the first is triggered by incoming camera frames, the second handles actuator control, and the third wireless communication. The main OS object handles the majority of tasks performed by the robot; it handles vision processing, localization and world modelling, and overall strategy. The actuator control object receives messages from the main object telling it the directions to look and walk. It then handles locomotion and joint control. The third object is designed to handle all data Input/Output from the robot, mainly through wireless communication.

In addition to the large scale breakdown into multiple OS objects. The internal structure of the main object was significantly changed. In previous UNSW teams long term behaviour, *e.g.* switching between forward and goal keeper, was changed at compilation time. Each of the long term behaviours was its own source file. In the current system, the behaviours have been consolidated into a single hierarchy and can be switched dynamically. They have also been broken into multiple source files. During this change, cleaner interfaces between the various modules were defined allowing the modules to be upgraded individually.

3 Behaviours

The consolidation of behaviours into a single hierarchy accompanied a major reworking of the behaviour of the rUNSWift team. While most aspects of the rUNSWift design philosophy for individual players remained the same, much more emphasis was placed on team co-operation. It is important to note that we do *not* equate team cooperation solely with a passing game. The close quarter cooperation among the robots was integral to behaviour of the team and is described in detail in the next section (Section 4). However, first we will describe the large scale behaviour of the robots.

rUNSWift's strategy relating to forwards was centred on aggressive play. Two design principles underly the rUNSWift strategy: first, a forward must strive to reach the ball ahead of the opposing team, and second, a forward should only attempt fine control of the ball if it has enough of a lead on the opposition to carry out that fine control, otherwise that player should concentrate on moving the ball upfield fast without worrying overly about the exact direction of movement. This is preferable to slowing down to reliably grab the ball for a front kick, because moving the ball upfield behind the opposing team stochastically increases rUNSWift's chances of scoring.

The aggressive play by the forwards is tempered by a mechanism, "dynamic role determination", which facilitates collaboration and minimises interference among the forwards. In "dynamic role determination", each of the three forwards assumes a role of attacker, supporter or striker depending on information that is shared by the robots, via wireless ethernet as well as visually, regarding each

robot's location, whether they see the ball, their proximity to the ball and their current role. An attacker is a robot that is currently playing the ball. A supporter is a robot that is supplying close-in support to an attacking robot. The striker is the robot providing long distance support, sometimes as a wing player on the far side of the field, and sometimes as a back.

When the Sony AIBO robots are in close proximity, they have a tendency for their legs to become entangled. To try and avoid this, an automatic "backoff" mechanism (see Section 4) is triggered when a forward's vision system detects that a teammate is in very close proximity. It is this backoff mechanism that controls the roles of the two robots nearest the ball.

The robot furthest from the ball plays the striker role, and moves swiftly towards a point on the field, determined by whether the ball is in the offensive half and whether it is in the left or right half of the field. If the ball is in its own (defensive) half, the point lies back from the ball near the robot's own goal; if the ball is in the target half, the point lies in the offensive quadrant opposite to where the ball is located.

rUNSWift's play strategy does not adopt the popular strategy of permanently having a forward remaining back in its own half defensively but instead favours the principle that defence is best achieved through offence and that it would be undesirable to lose the resources of an active third forward. This strategy leaves rUNSWift exposed to an extremely problematic situation that arises when all three forwards are on the wrong side of the ball and opponent robots have possession of the ball. In the Robocup 2003 final against UPenn, rUNSWift found itself in such a situation several times because the UPenn forwards had a kick that successfully flicked the ball past rUNSWift's forwards.

rUNSWift developed a defensive behaviour to counter this problem: the forward with the greatest offset across the field from the ball quickly rushes to position itself behind the ball, while the two other forwards rush directly towards the ball. This defensive behaviour is dynamically triggered when all three forwards are on the wrong side of the ball. The behaviour is effective because when this situation occurs, an opponent robot is likely to be either closer to the ball than the forwards or is between the forwards and the ball. If all three forwards rush directly towards the ball, they will either become blocked by opponent robots or become entangled with one another. In order to ensure effective defence, one of the forwards needs to quickly get back to its own half, between the ball and its own goal to block a possible goal. As it is important that this robot does not become entangled or taken off the field, it circles around other robots and travels along the boundary of the goalbox if it finds that its path would otherwise travel through it.

4 Local Robot Interactions

In addition to possessing a global form of cooperation between the robots, where a third robot is placed apart from the main two forwards, the close-in cooperation and local interactions are an important feature of the UNSW/NICTA strategy.

The two robots closest to the ball do a lot of shifting and reconfiguring of their positions relative to the ball and one another as they chase the ball. Collectively, this allows them to better maintain possession and control of the ball, as the robots support one another and take turns attacking the ball. Typically one robot will be attacking the ball, and the other will be closely supporting, getting ready to take over the attack. This is mostly used in overcoming the opponents' defensive moves. When the original attacking robot runs into the opponents' resistance, the supporting robot will then take over the attack.

As delays of 500ms were common in the wireless communication system, this close-in cooperation was heavily reliant upon vision to verify the last known position of a robot's teammates. If a robot cannot see any of its teammates, it will simply attack the ball. However, when a robot can see a teammate, a decision is made to determine whether it should attack the ball, or support the attack. This decision is made based on three aspects: the robots position relative to the field, the ball and its teammates. The overall effect is subtle but exceptionally effective.

This strategy uses the concept of "Desired Kick Direction" (DKD) from previous UNSW teams. Depending on where the ball relative to the field, the robots will want to move the ball in a different direction (See Fig. 1a). This desired direction will help in determining which robot is in the better position relative to the ball, and thus which robot should attack the ball. Generally, the DKD is away from the robots own goal, and towards the target goal.

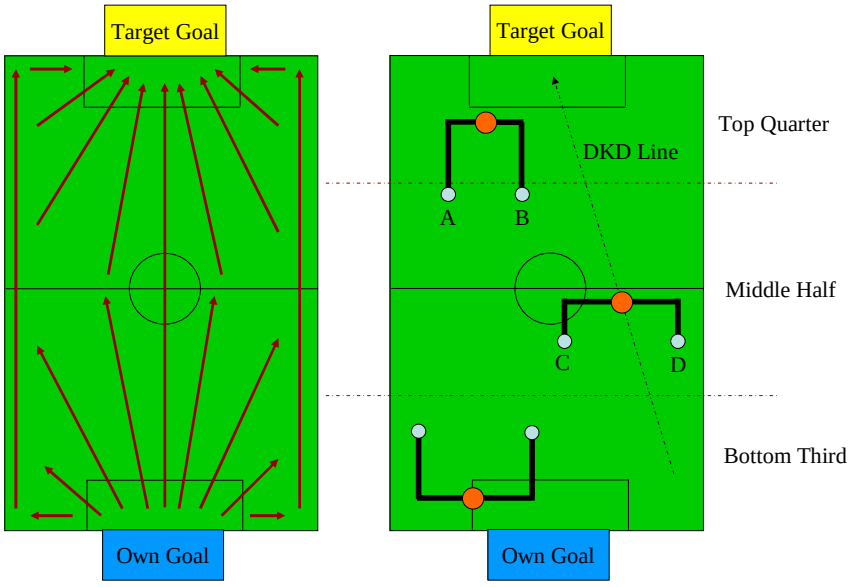


Fig. 1. (a) Desired Kick Directions (DKD). (b) Various "L" support positions.

After the DKD has been determined, we draw a star, centred on the ball and pointing in the direction of the DKD (see Fig. 2). This splits the area around the ball into regions, and it is the teammate's positions relative to each other on this star that determines which is to attack and which is to support. The details of this algorithm are shown in Table 1.

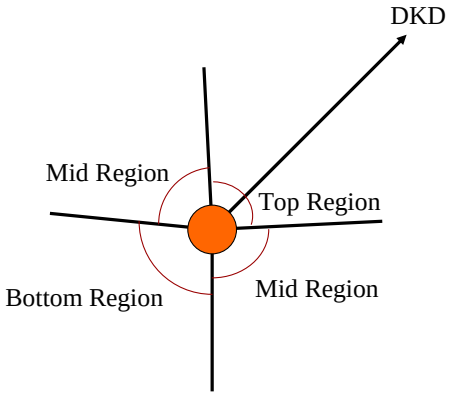


Fig. 2. Star, dividing the area around the ball into regions

The final major component in our local cooperation strategy is the close-in support/backoff position. If the robot is not attacking the ball, it will position itself to prevent the ball from travelling towards the defending goal, and to get ready to take over the attack towards the target goal. This position is based on where you are on the field, and relative to the position of the ball (See Fig. 1b).

If the ball is in the top quarter of the field, the supporting robot will position itself in an "L" shape to the side and behind the ball, such as that depicted by points A and B. The robot will go to point A or B depending on which side of the DKD line it is on. If it is to the left of the line, it will go to the left most position, *i.e.* A, otherwise it will go to point B. The reasoning behind this is that this will keep the dog from obstructing goals by travelling between the ball and the target goal. Probabilistically, it will also have the dog travelling to the closer support position, and it will have the dog closer to the centre of the field, and between the ball and its own goal. The support position is back more than it is to the side. This is so that the supporting robot will more often be behind any loose balls, ready to take over the attack.

If the ball is in the middle half of the field, the supporting position will be in a wider "L" shape such as that depicted by points C and D relative to the ball. Again the robot will choose between points C and D depending on which side of the DKD line it is on. The "L" is wider here so that the supporting robot is wider, ready to intercept sideways passes.

In the bottom quarter of the field, *i.e.* the defensive quarter, the support position is in an "L" shape in front of the ball. Instead of positioning itself

- If a robot is in the bottom region of the star, and the other robot is not, then that robot will attack the ball and the other robot will go to the supporting position.
- If both robots are in the top region, then the one who is closer will attack the ball, and the other will get out of the way as the closer robot will probably perform a 180 degree kick. After getting out of the way, that robot will move into the support position.
- If both robots are in the bottom region, then the robot to attack the ball is determined based on the following:
  - Which robot can actually see the ball. (as opposed to wireless knowledge).
  - Which robot is closer to the ball.
  - Which robot is closer to the DKD.
  - Which robot has the lower player number.
- In all other cases both robots will closely circle around the ball towards the DKD until one stops seeing its teammate, and thus is free to attack the ball, or one enters the bottom/attacking region. Circling around closely allows the robots to maintain a defensive position relative to the ball.

Table 1. The algorithm for deciding the role of a robot.

defensively between the ball and the defending goal, it is away and in front of the ball. This is so that the support robot stays out of the attacking robots way, minimizing the chance of getting leg locked with that robot and inhibiting the defense. It is also then able to capitalize on any opportunities where the ball becomes momentarily loose from the opponent attacker.

An emergent property of the up field "L" shape in the bottom third of the field is that the two robots tend to move in a circular path around the bottom corners (See Fig. 3a).

Typically, the attacking robot will be in the in the bottom corner trying to stop an opponent from progressing any further with the ball. Meanwhile, the supporting robot will wait in the supporting position. As the first robot loses control of the defense and moves out of the bottom region of the "star shape", the supporting robot will take over the attack and the first robot will then assume the support position. In this way, the robots exchange positions, moving in a circular fashion until the ball is out of the corner.

A special case that needs to be discussed is what happens to the supporting position when the ball is near the side edges. In this case, the supporting position will be against the side edge and behind the ball (See Fig. 3b).

Often the attacking robot will get into a scrum on the side wall with one of the opponent robots. In the case where the opponent robot wins and gets the ball past the attacking robot, the supporting robot is there as a second line of defense to stop the ball from advancing to far towards the defensive goal, and as a second chance to clear the ball.

The behaviour of local cooperation in the UNSW/NICTA strategy is a result of having Desired Kick Directions, Star shaped region dividers, L shaped support positions and the ability to visually see teammates and opponents. It is the combination of local cooperation skills and global cooperation skills that results

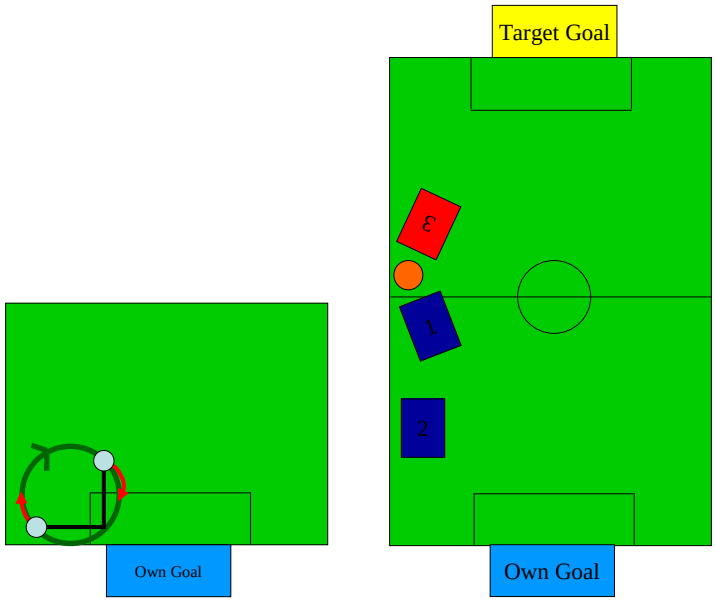


Fig. 3. (a) Corner, and (b) side defensive locations

in an effective team strategy. Although to the unfamiliar eye, the behaviour may not be obvious, the behaviour, subtle as it is, is quite deliberate, planned and effective.

5 Vision Overview

The vision system used in 2003 is very similar to that used previously. Information from the CMOS camera is processed by first identifying the colours, then forming coloured blobs, combining the coloured blobs to form objects and finally calculating the location of objects relative to the robot.

rUNSWift 2003 used replaced the nearest neighbour algorithm from 2002, with a table generated using the C4.5 decision tree inducer as it was found to be less susceptible to lighting changes. Neither method was found to be entirely satisfactory, so it was also necessary to fine-tune the result with a manual classifier.

Ball localisation close to the robot gained more importance this year due to the heavy emphasis on close-in interactions. As the close-in interactions require accurate recognition of the ball's position when a large portion of the ball would reside outside of the camera frame, a new method was introduced that could determine the centre of the ball by applying circle geometry and edge detection. Once the centre is accurately determined, the ball's location is calculated by

projecting the ball centre onto a plane parallel with the ground plane. For far away balls, distance is determined by the width of the bounding box.

Beacon detection is unchanged from previous years. The relative positioning of colour blobs forms the basis of beacon recognition. Given the location and size of two colour blobs, a series of logical deductions are made to determine whether they form a valid beacon. Distance to the beacon is determined by taking the Cartesian distance between coloured blobs centroids, and an equation that maps centroids distance to world distance is then applied. The Cartesian distance above all else was used because it is found to be least susceptible to different colour calibrations. Geometric transformation was found not to be a viable solution due to inaccuracies in the robot's joint readings ($\pm 5^\circ$), which could introduce a significant error over large distances.

Goal recognition is similar to beacon recognition, but distance is determined by goal height. Because the goal often intersects with the top camera frame, simple height extensions based on the width of the goal is applied.

While detection of beacons and other objects is largely unchanged from previous years, the filtering of false positive identifications was significantly changed. These filters have traditionally been hand crafted after watching the behaviour of the robots. This year a more structured approach was taken. A port of the vision module that can be executed offline using logs taken from the robots allowed the filters to be tested with large sets of sample images. This system shows both over and under-filtering quickly, as well as allowing the identification of which rules are causing over-filtering. Originally intended for development of sanity checks, this offline port have introduced improvements to development and debugging time in other areas, including both the ball and edge detection challenge.

6 Object Tracking

The agent's internal model of the world allows it to track it's own location on the field, as well as the location of the ball, it's teammates and opponents. This section of the rUNSWift team was entirely re-written this year using extended Kalman filters. The location of the robot itself was tracked with a single 3D Kalman filter over X, Y, and θ. The location of the ball was tracked, along with its velocity, in a pair of 2D Kalman filters. Finally, the opponents were tracked using a set of four filters on each robot. These final filters shared information between allied robots using distributed data fusion.

Tracking opponent robots is inherently difficult since the visual detection of robots is relatively poor, and the observation frequency is low. Our aim is to track the approximate position of the opposition team, hence we are not interested in fine accuracy as we would be with our own position, or especially in the case of the ball. For these reasons we developed a distributed sensor network for opponent tracking. This consists of multiple sensor nodes (*i.e.* our team's robots), which are connected with a temporal constraint, since our robots do not communicate every frame (the cycle period of the sensor), but rather wait for a period of several frames. The processing of the network is also done in a

distributed fashion, with each node keeping it's own model of the opponents' positions. The model we developed is based on Information Form Kalman Filtering.

6.1 Information Form Kalman Filter (IFKF) Algorithm

For a full introduction into Information Form Kalman Filtering see [4]. This work extends that work through adaptation to non-linear observations. The information form Kalman filter algorithm is a recasting of the basic Kalman filtering algorithm. The data contained in a Kalman filter, expected value $\underline{x}$ and covariance matrix $\underline{\underline{Q}}$, can be represented in the form of inverse covariance times expected value $\underline{y} = \underline{\underline{Q}}^{-1}\underline{x}$ and inverse covariance $\underline{\underline{Y}} = \underline{\underline{Q}}^{-1}$, known as information form. By doing this, and rearranging the update equations accordingly, we obtain a system mathematically identical to a Kalman filter model where updates are of the form

$$\underline{y}(k|k) = \underline{y}(k|k-1) + \underline{i}(k)$$
$$\underline{\underline{Y}}(k|k) = \underline{\underline{Y}}(k|k-1) + \underline{\underline{I}}(k)$$

where $\underline{i}(k)$ and $\underline{\underline{I}}(k)$ are the updates due to observations at time k. This provides a distinct advantage over regular Kalman filtering, in that estimations are formed from linear combinations of observation information. Hence if sensor n last sent distributed update data at time k-α, then it simply sends $\sum_{j=k-\alpha}^{k} \underline{i}(j)$ and similar for $\underline{\underline{I}}$, as an update to the other sensors. Therefore, ignoring the complexity of synchronization of updates, all sensors should hold the data (assuming N sensors)

$$\underline{y}(k) = \underline{y}(k-\alpha) + \sum_{n=1}^{N}(\sum_{j=k-\alpha}^{k} \underline{i}_n(j))$$

and similar for $\underline{\underline{I}}$. This solves a key problem in decentralised data fusion, all nodes hold equivalent data in the long term. We also mentioned that the information form of the Kalman filter is mathematically equivalent to the regular Kalman filter, therefore the estimation held by all the nodes is equivalent to the estimation made if a single node was to receive all observations by all nodes combined.

6.2 Observation Matching

The algorithm described above solves the problem of having multiple sensor nodes with our temporal constraint, however the task of tracking opponent positions still holds other issues. Tracking a team of four opponents requires the estimation of four positional vectors, this indicates that four separate information Kalman filter models need to be used, or a similar approach applied. This leads to a very elementary problem, given an observation, and that all opponents

look identical, which model should be updated? There are two simple solutions to this problem, both of which were tried.

The first solution is arguably the logical one, choose the most probable model. This approach can be realised through the equation

$$P(O|G_n) = \frac{1}{2\Pi\sqrt{|\underline{\underline{K}}|}} e^{-\frac{\underline{x}^T \underline{\underline{K}} \underline{x}}{2}}$$

where O represents the observation, G_n the nth gaussian probability distribution, $\underline{x}$ the innovation vector and $\underline{\underline{K}}$ the gaussian covariance projected to observation space. By choosing the gaussian with the largest of these probabilities, and updating it's Kalman filter model with the observation, we can match individual observations to individual models. Although this solution is perhaps the mathematically precise one, it suffers from several problems, the most severe of which is that some gaussians reach outer limits, growing very large, and end up not winning any observations, while other gaussians win alot of observations and hence "bounce" between observations.

A variation of the above is to use the same algorithm, except instead of using the probability of the observation given the gaussian, use the number of standard variations away from the expected value the observation is, this is given by $e^{-\frac{\underline{x}^T \underline{\underline{K}} \underline{x}}{2}}$. By using this value instead gaussians that do not attract observations, grow in variance, and hence have a much greater chance of "winning" an observation. However this method still does not offer adaptation to an opponent's positions quick enough, suffering especially in the kidnapped robot situation.

The second simple solution to the problem of observation matching is to "share" the observation around. We can apply a fraction of an observation to a gaussian in the IFKF by multiplying the variance of the observation by the inverse of the fraction. Hence we can alot a weight for each gaussian (n)

$$w_n = \frac{P(O|G_n)}{\sum_{i=1}^{N} P(O|G_i)}$$

and apply the fraction of the given observation to the IFKF. This solution leads to a set of models that can very quickly adapt to changes in the opposition's positions as gaussians quickly move from areas where there are no observations to places of high observations. However the solution also leads to problems of multiple gaussian distributions becoming extremely similar, at which point they are very unlikely to separate.

After analysing the two simple solutions discussed, we can see that both have their problems. Ideally the solution should have the ability for models to adapt to sudden changes in opposition position's that the second method offers, while maintaining a reasonable spread of gaussian distributions that the first method has. The logical step was to try to create a hybrid method which combined the two, and hopefully inherits both ideal behaviours. By using the calculated weights above, we can create a new weighting system taking both methods into account. The new weight v can be calculated by

$$v_n = (1-\alpha)w_n + \delta_{nj}\alpha$$

where w_n is the original weight, j is the "winning" gaussian calculated using standard deviations, δ is the Kronecker delta and α is a constant between 0 and 1. In fact if we take α as 1 we get the first solution, and as 0 we get the second. We can see this solution takes a portion of the observation and assigns it to the "winner", then breaks the compliment portion into pieces according to the second solution. This hybrid solution works extremely well, providing a highly adaptive set of distributions while maintaining a spread over all observation areas. It of course still inherits some of the problems that the initial solutions had, and it certainly would not be reasonable where acute accuracy of positions was required, but it succeeds in our initial goals, providing a good approximation of the opponent's positions, representing observations from all teammates.

7 Automatic Gait Optimisation

A major innovation made by the UNSW/NICTA entry this year was automatic gait optimisation (see [2] for more details). This was the first such technique seen in the competition and resulted in improvements in speed and stability over previous hand-crafted gaits. The technique learned fast enough to run on-site at the event during the allocated practice days before the start of competition matches.

7.1 Background

This work was built on top of the locomotion module from previous years, originally developed by the year 2000 UNSW team. The walking component of the locomotion module was designed on the concept of a rectangular walk locus; this is the trajectory traced out by the robot foot as it walked [5]. It was parametrised by three movement parameters for omnidirectional control, one speed parameter that controlled the rate at which the paw moved around the locus, and eight stance parameters. These parameters were used to define the four corners of the rectangular locus, as well as the position of the loci relative to the robot body.

A variation of the walk locus used by the 2002 UNSW team was a trapezoidal locus. This was designed to reduce the slowing effect caused by the claws on the rear feet of the robot catching on the carpet surface. This change resulted in a significant speed increase of approximately 12% over the rectangular locus, but it was found that it was much less manoeuvrable and not very smooth. For these reasons, both gaits were used, with the strategy determining when it was suitable to use a particular gait.

This work builds on these previous gaits by exploring the space of quadrilateral loci to find an effective gait. This automation has two effects: we are able to find a more effective gait than used previously, and we are able to optimise that gait for a particular walking surface. As with the 2002 architecture, the new walk was only used for walking forward, with no sideways movement component and less than $15°s^{-1}$ turn.

7.2 Problem Representation

The problem representation was formulated with the intent of restricting exploration to small local changes to the walk locus. Large changes were not considered as it was known from previous years that effective walks existed in the space being searched, and small changes both increase search speed and minimise disruption to other tasks, such as localisation, that may be dependent on characteristics of the previous walking system.

The new quadrilateral walk locus is described by four offsets from the original rectangular locus, and the speed of the robot foot around the locus is constant. Using the original locus as a base allows all of the existing speed and turn controls to carry over to the new gait. In order to explore this search space, each of the offsets can be moved in three dimensions – either forward or backward, sideways, and up or down. Since there are four corner points in a quadrilateral locus, this produces a 12-dimensional vector representation. This was then extended by using different loci for front and rear pairs of legs, resulting in a 24-dimensional vector representation.

The basis rectangular locus is positioned relative to the robot body using the same low forward-leaning stance used by the UNSW team in past years. Specifically, this places the centre of the front locus 60mm in front and 5mm out sideways from the shoulder joint, and the centre of the rear locus is positioned 55mm behind and 10mm out sideways from the hip joint. The shoulder and hip joints are raised 70mm and 110mm from the ground respectively. The result of this is a quadrilateral locus shape in three dimensional space.

7.3 Experiment Environment

The experiment environment was largely based on the setup used by Hornby et al. [6, 7]. The robot walks back and forth between two landmarks, and the optimisation method tries to minimise the time required.

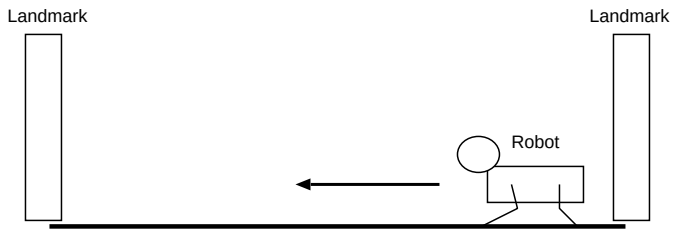


Fig. 4. The experiment environment.

The landmarks used in the experiment were the two beacons at either end of the middle field line. To determine when the robot has reached a landmark, a combination of visual distance estimation and infrared distance reading are used.

Once the robot determines that it is within a pre-defined distance of the target landmark, it stops, turns around and lines up to face the opposite landmark, and begins the next trial run. The environment is shown in Figure 4.

The time measurement was based on the camera frame rate and execution cycle of the robot. The camera receives 25 frames per second; a count of the number of camera frames processed is kept as the robot walks from one landmark to the other. The goal of the optimisation process then is to minimise this amount. Given the fixed distance walked, minimising time corresponds to maximising speed.

There were two main sources of stochasticity in this experiment. Specifically, they were:

- Error in distance measurement from sensors – this may cause the robot to stop either too early or too late in front of the target landmark. As a consequence, the distance walked on each trial is not exactly the same.
- Error in positioning – the distance covered could also turn out to be different if the robot ventured slightly off course. While the robot was programmed to head straight towards the landmark, some error in sideways shifting was present.

In particular, the error in distance measurement was greatest when a bouncy walk was produced. A bouncy walk had the side effect of shaking the robot head, which would result in the sensors producing inaccurate distance readings, and would thus tend to end trials prematurely. To work around this problem, the robot stopped briefly after each trial to settle, and then re-measured its distance to the target landmark; trials that fell short by more than a certain threshold were penalised.

To reduce the effect of stochasticity, a single measurement of gait speed was implemented as four separate runs between the landmarks. The average of the two median readings was used as the evaluated time. This meant that measurements would take more time, but allowed us to use a non-stochastic optimisation technique.

It should also be noted that while the robot was mostly walking straight forward, it was applying small corrections to its heading to reach the destination landmark. This had the important effect of introducing small amounts of turn into the evaluation of the walk. The final walk was quite robust to small amounts of turn.

7.4 Optimisation Method

With the problem representation and experiment environment established, the problem has been reduced to one of multidimensional optimisation and many algorithms are applicable. A major restriction is that gradient information is not available.

We expected the search space to be relatively smooth, and the method we chose to employ was Powell's (direction set) method for multidimensional minimisation, as outlined by Press et al. [8]. Powell's minimisation method starts

with a set of directions in the multidimensional space, minimises along each one, and notes the effectiveness of each direction. It then uses that to derive new directions, with the intention of finding directions that minimise the function quickly.

As stated previously, the locus is represented as four corner points of the quadrilateral, and each point can be moved in three dimensions. Using different locus shapes for front and rear pairs of legs, this adds up to a 24-dimensional search space. Instead of using the set of unit vectors in the search space as the initial direction set, we chose a different set with the intention of exploring the search space more efficiently. This was a linear transform of the set of unit vectors, i.e. we can reach any point in the space using a linear combination of this set of vectors.

The directions are shown in Figure 5. They are divided into three partitions of eight directions each. Each partition shifts the loci in a certain physical directions. Note that when minimising along each direction, the values found for each direction may be positive or negative. In other words, the physical movement of the locus points for each minimisation direction may be in the directions shown or they may be reversed.

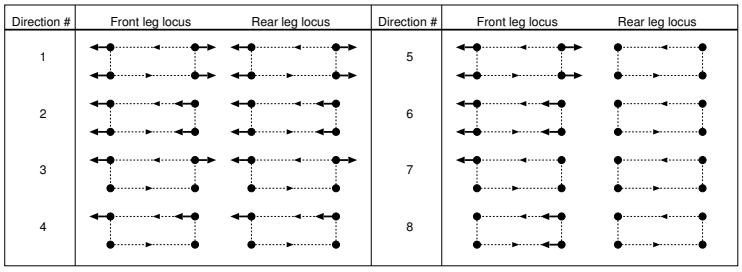
7.5 Other Experimental Details

The minimisation method was run at the 2003 RoboCup competition. Unfortunately, due to preparation time constraints at the venue, we were not able to run the method through to complete convergence. We were able to get through minimisation along 22 of the 24 dimensions. At one point during the minimisation we noticed that the robot seemed to be stuck in a poor local minima, and so we restarted that particular line minimisation. It did not get stuck in the local minima the second time. We believe the minima was an artifact of noise in the robot's measurements. Also, a programming error in the code resulted in some different minimisation directions. This inverts the two points on the right hand side of the rectangles in Figure 5. Note that this is a linear change in basis and the modified basis set can still reach every point in the search space.

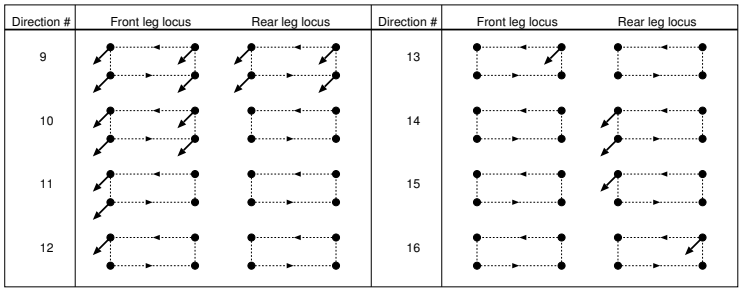
7.6 Results

The loci produced by the minimisation technique are shown in Figure 6 and Table 2. The offsets in Table 2 are added to the $x-y-z$ positions of corresponding corner points in the original rectangular loci to produce the final loci. For example, locus point 1 corresponds to the bottom right corner point of the front locus. To calculate the shifted position of locus point 1, the bottom right corner point of the front locus in the basis rectangular locus is shifted back 3.64829mm, 4.65264mm outward, and 5.44244mm downwards.

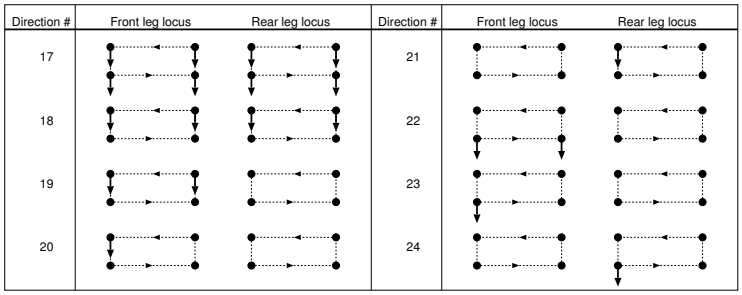
In general, the walk tended to take long forward strides with the front legs, with the sideways spread reducing in towards the body when stretching forwards and spreading outwards from the body when pulling back. The rear legs took large, high steps forward, with sideways spread reducing in towards the body



(a) Forward/backward directions: these directions have the effect of modifying the horizontal length of the locus.



(b) Sideways directions: these directions have the effect of either bringing the locus closer towards or further outwards from the robot body.



(c) Vertical directions: these directions have the effect of either raising or lowering the height of the locus.

Fig. 5. Search directions used for manipulating the locus with Powell's method.

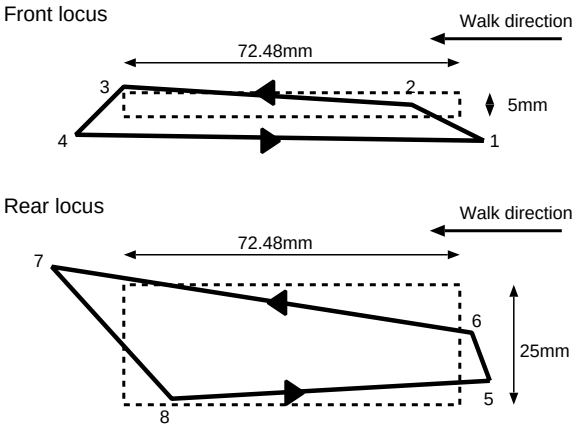


Fig. 6. A side view of the loci produced by the minimisation technique, shown in bold. The dotted lines show the basis rectangular loci.

Locus Point	Forwards offset (mm)	Sideways offset (mm)	Vertical offset (mm)
1	-3.64829	4.65264	5.44244
2	9.40879	-2.16859	1.80812
3	0.50342	2.12128	-0.298782
4	7.92933	10.6357	4.47817
5	-6.30445	-4.70413	-5.22602
6	-2.58385	14.6642	10.4322
7	13.8908	2.5354	-4.09243
8	-8.3251	-1.80062	-1.51026

Table 2. The offsets learned by our optimisation procedure.

when pushing back and spreading outwards from the body as the legs were raised and brought forward for the next step.

The speed of the gait was measured at $27\text{cm}\,\text{s}^{-1}$. This was significantly faster than the previous hand-developed trapezoidal walk locus on the particular surface used at the competition. In addition, the minimised locus was considerably smoother than the trapezoidal locus, and kept the robot's camera steadier. This had helpful effects on other tasks required to play soccer effectively, such as distance and velocity estimation and localisation.

To evaluate the effectiveness of the technique under more controlled conditions, the walk produced by the technique at RoboCup was compared with the hand-crafted trapezoidal locus and rectangular locus walks in our lab. The comparison was run on a similar surface to that used at RoboCup, timing the robot over a distance of 1 metre, over 50 trials for each walk. The rectangular locus was the slowest, as expected, with an average speed of $22.69 \pm 0.45\text{cm}\,\text{s}^{-1}$. The trapezoidal locus was next, measured at $25.42 \pm 0.50\text{cm}\,\text{s}^{-1}$. The walk produced at the competition came out as the fastest, measured at $26.99 \pm 0.50\text{cm}\,\text{s}^{-1}$.

8 Challenges

In addition to the main robocup competition, there were three technical challenges which teams competed to complete at RoboCup 2003. These were to walk the length of the field avoiding other stationary robots, to kick a black and white ball, rather than the normal single-colour orange ball, into the goal, and finally, to move to each of five separate points on the field in turn without the aid of markers around the side of the field.

8.1 Obstacle Avoidance

To complete the first challenge, the robot is given an additional internal representation of the world in the form of a grid. When an obstacle is detected, it is placed into this grid. A reinforcement-learning framework is applied to this information, thus determining action policies for the robot. This action policy maps grid-squares to the direction in which the robot should travel to achieve its goal.

When an obstacle is seen through the robot's vision system, its location in the world and its existent probability are calculated. This information is then recorded in the robot's internal world model.

When a previously detected obstacle cannot be seen when it should be visible, its existent probability decays. Prolonged unseen period of an obstacle will result in it being removed from the world model. This step is done to overcome reliability issues in the robot's vision system.

The reinforcement-learning framework consists of a set of states and a set of actions for each state. At any time, the robot is in a state S and it must choose to take an action A, upon completion of the action, the robot will result in a

state S' and receive a reward R. When determining its next action, the robot should aim to maximise the cumulative reward.

Each grid in the world model is a state in the reinforcement-learning framework, there are eight possible actions that a robot can do in each state, that is, moving in the eight basic directions. The reward scheme is defined such that the robot will result in severe penalty if it collides with an obstacle, moreover, a small penalty is awarded to the robot for each action it takes, so that the robot would learn to reduce the number of actions it needs to achieve its goal, thus result in a shorter path through the obstacles.

Since the action policies are discrete and the real world is continuous, to smooth out robot movements, the actual motion of the robot is determined by combining the policies of the four grids closest to the robot's location. The policies are translated into vectors where the direction of the vector is the direction of the policy, they are then combined by calculating their vector sum.

8.2 Black-and-White Ball Detection

In order to detect pixels that have a high probability of forming part of the black-and-white ball, each pixel in the colour-classified image was examined for such characteristics as classified colour, number of white classified pixels in the immediate vicinity, number of green classified pixels in the immediate vicinity and the like. These criteria were developed by trial-and-error, however future development may allow a machine-learning approach to this problem.

Spatially dense clumps of these so-called 'interesting pixels' were then found using an Expectation-Maximisation based algorithm. The spatial average position of all these interesting pixels was first determined. A weighting function was then applied to all interesting pixels, centred at this average position and scaled based on the average distance of all pixels from this average position. The weighted average spatial position was then found and the process repeated until convergence.

It was found that at short range this algorithm would converge to single spots on the ball. As a result, a second, similar processing stage was applied but with the weighting function scaled based on the expected apparent size of the ball. This improvement was found to be effective in causing the algorithm to converge to the actual ball position at middle to close distances.

Once the position of the ball in the image was found, a geometric transform was applied to find the position of the ball relative to the robot, based on knowledge of the camera position and the fact that the ball lies on the field. Various heuristic 'sanity checks' were then applied before the parameters of the ball were passed onto the behaviour subsystem.

Finding and Manipulation The traditional rUNSWift frontkick, chestkick and turnkick were found to be ineffective on the challenge ball due to its variable size and surface texture. However, due to the relative softness of the ball, it was found that by bringing the front paws inwards, it was possible to run into the ball

and kick it forwards with reasonable accuracy and force, even if the approach to the ball was off-centre.

8.3 Edge Detection and Matching

Over most of the field, it is possible to localise based on triangulation off the two goals, using largely existing infrastructure and some data smoothing. However, In order to provide localisation information when too close to a goal, a visual edge matching algorithm was developed. Firstly, the edges between white and green classified pixels were found. This search was limited to areas of the image that corresponded to locations on the field closer than 2 meters. These edge points were filtered for noise and randomly culled to leave about 20 to 30 edge points.

A geometric transform was applied to these points to find their position on the playing field, based on knowledge of the camera position and the fact that these points intersect the ground plane. Once these points are found, they are converted to global co-ordinates based on the current best-guess position (obtained via triangulation of the goals and odometry). A lookup table was then used to determine the distance between the projected points and the nearest consistent feature, such as a field line or field edge and these distances summed to form a cost function. A spatial offset was applied to all the points and the cost function recalculated. This process is repeated for a number of offsets in the two translational and one rotational dimension to find the one that results in the lowest cost function. This represented the position that explains the current observation with the highest probability and was taken as the best 'match' position. This process was then repeated using successively smaller offsets and using the lowest cost position of the previous iteration as a starting point, until the required accuracy is obtained. This algorithm was referred dubbed 'NightOwl'.

Behaviour Three broad behaviours were developed in solving this challenge. The first routine localised in the absence of any previous localisation knowledge by facing one goal, turning the body whilst tracking that goal then panning to face the other goal, turning around if the angle was too large (as would be the case if the robot were facing out of the field). Simple triangulation was used to determine the location based on this observation. The second routine involved keeping the robot facing across the field whilst panning the head left and right to observe the two goals. Distance and heading measurements from each goal were added to a Kalman filter which would track the robot's position whilst it was moving. Finally, when the desired point to move to was too close to a goal for an accurate measurement, the NightOwl routine would be invoked which would look down at the field, near the goalbox, and attempt to perform edge matching to obtain localisation.

9 Conclusion

Significant development occurred in the rUNSWift team this year along a number of lines. Software engineering process improvements as well as code re-structuring allowed the team to progress in a number of different directions.

The overall strategy of the team was re-implemented with a strong focus on cooperation of two forwards working in close proximity. A new method of ball localization was used when the ball was close, and hence partially out of the camera frame of the robot. New tools were developed for building filters for objects returned by the vision code. Tracking of objects was made mainstream using Kalman filters. In addition, opponent localization was significantly improved with distributed data fusion. For the challenges, a system using edges and lines on the field to localise the robot was developed and used to aid localisation during games. Finally, automatic gait optimization was used to improve the forward walking speed of the robots. The result of all these improvements was a high effective, world champion, robot soccer team.

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