System Design Project 2011
Team 9 – Robotniks
Final Report

Khurram Aslam
Christopher Connelly
Alice Elder
Callum Lewis-Smith
Dave Pilling
Mitul Bhakta
Simonas Dirvanskis
Elias Kunnas
Yannick Novella
Lynne Wallace

Abstract - This report aims to give a detailed overall description of the system we implemented as well as giving critical analysis of our performance and insight into how future SDP groups may further develop and learn from our system.

Overview

The objective of the System Design Project (SDP) was to build a robot that can play Robocup-like soccer competitively using a 10-person team. The first probleim faced in SDP is to come up with a way to efficiently use the available resources (manpower) and to channel the development effort so as to prevent duplication of effort as well as minimising the interdependencies between the sub-systems to reduce the communication costs.

System Architecture

Though our initial design and system architecture slowly evolved over time, there were no dramatic differences between the first and the final architecture of our system. We decided to first posit a number of sub-systems and high-level interfaces between them. Doing this helped organise our overall development effort. The final system architecture is illustrated in Figure 1.

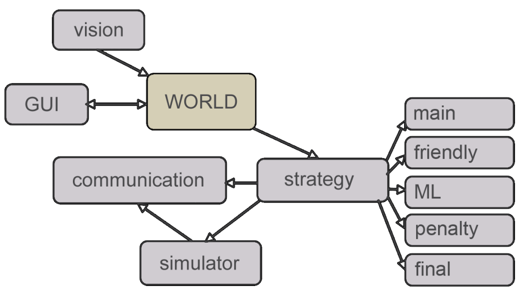


Figure 1: The system architecture and the information flow between the various subsystems. The links from the strategy subsystem are examples of the different strategies that the system could be instructed to run. Not shown are the vision-camera links and the communication server - robot links.

Management and Organisation

After looking at past SDP projects to get a flavour of how they managed the team we initially decided not to use a specific management technique but rather adopt a more democratic approach. The team was split in line with our outlined architecture, i.e., into groups focused on robotics, vision, communication, and strategy, respectively. This assignment was done based on individual preference and most of the decision making was left to the respective subgroups.

The more relaxed approach seemed to be going very well up until the poor performance during the first milestone. After the subsequent meeting with the team, it was clear that most individuals were not aware of how other subgroups were progressing and that more emphasis towards integration testing was needed. The frequent meetings were a key reason for subsequently choosing SCRUM over other methodologies. Although meeting everyday was sometimes not practical, we tried to ensure that everyone, be it as a whole group or a subgroup, met at least three times a week. Further to this, each member had a development diary which they would use to document their work and allow any people who missed the meeting to keep up to date with our progress. The added formality of SCRUM greatly improved the efficiency of our work.In particular, the use of pair programming meant that the less experienced programmers in our group could be paired with someone who could more readily translate their ideas into code.

Planning and Progress

The progress management broke down into two key aspects: What had to be done, and what would happen if we didn't do it.

The first step was to create a Google Docs spreadsheet. which contained information about what had to be done, how important is was, its current status, and who was carrying it out. These tasks were assigned and discussed during our regular SCRUM meet ups.

The second step was to consider the risks involved with certain tasks. We used a risk management chart (Figure 2) for this with the aim being to classify each potential stumbling block based on likelihood against severity of occurrence. This helped us to en-

Work Area	Risk Factor	Impact on Project	Risk Rating	Risk Plan				Severity	
Vision	Vision is not working on both of the pitches	Would compromise the whole project	LH		Probabilty		L	M	H
Robot	To much friction between wheel and pitch	Robot cannot move in a straight line	LL	Install ball bearings		L	LL	LM	LH
Robot	Communication between RCX and NXT	Could only send basic movement commands	LM			M	ML	MM	MH
Robot	Taking Battery out of RCX to recharge would require reinstalling everything again	Estimate time to reinstall is around 20minutes so we would need to take much longer between each game	MH	Give ourselves plenty of time between charging and playing		H	HL	HM	HH

Figure 2: Risk Management

sure that any tasks in the red were handled immediately and with due care.

Robot Design

When it came to the design of the robot it was decided that we would aim to create an innovative design with the aim of improving on the efforts of previous robots.

Looking at designs from the previous years of the course we realised that the best robots:

1. were *manoeuvrable*, allowing for quick and direct movement to the ball,
2. had *strong kickers* to allow for powerful kicks right across the pitch and off the side walls,
3. were built with *strong chassis* to put up with aggressive game play, and
4. were *simple* , making it easy to write their control system software.

Of these key areas, we decided to focus on manoeuvrability and strength, deeming them the most important.

The last years recorded games indicated that much time was wasted by the need for many robots to stop and turn before they could move to the ball. A design that could move to the ball directly would have a big advantage against these traditional robots.

Having established the need for an agile and manoeuvrable robot, we needed to find a suitable wheel design. The majority of past designs made use of two conventional static wheels placed on either side of the robot's chassis; the wheels would be individually powered in order to move and turn the robot.

The Traditional Wheels

Static wheels are conceptually simple, reliable and cheaply implemented using the standard Lego NXT kit. For all their advantages, static wheels dont allow for direct movement to the ball in general, since the robot has to be either stopped and turned or turned by moving the wheels on different sides by differing amounts.

In addition to the challenges with steering, in order to maximise the manoeuvrability that can be achieved using static wheels very large wheels were required to reduce the overhangs at the front and the rear of the chassis. Larger wheels reduced chassis space and this would make it harder to fit in a powerful kicker design.

Tank-Style caterpillar tracks offer another way to eliminate the problems associated with big wheels. As well as reducing the space required for large wheels, they could in theory also provide better grip on rough surfaces due to the increased surface area in contact with the ground.

However, contrary to past years, this years painted pitch surface is very smooth, and consequently many groups experienced problems with grip using caterpillar tracks, which made tank tracks unsuitable for a high-performance design.

Besides the grip issues associated with caterpillar tracks, a robot fitted with them still had to stop and turn in order to move to a direction perpendicular to it. This limited their potential for manoeuvrability of a track-equipped robot similar to one with static wheels.

Omni wheels were the solution chosen by the 2010 winning team in order to maximise manoeuvrability and to get around the need for having to stop and turn. Omni wheels are holonomic, allowing direct movement in any direction. The omni wheels are made up of a set of rollers positioned around the circumference of the wheel, allowing for movement that is perpendicular to the wheel's axis of rotation.

By using four powered omni wheels, the 2010 wining team created a robot platform which could move in any direction without turning while still allowing their robot to rotate around it's own axis. Although these wheels seemed very appealing for maximising the manoeuvrability of our robot, they had some drawbacks:

1. Omni wheels are complex and many pre-2010 groups struggled to make their robots move with them,

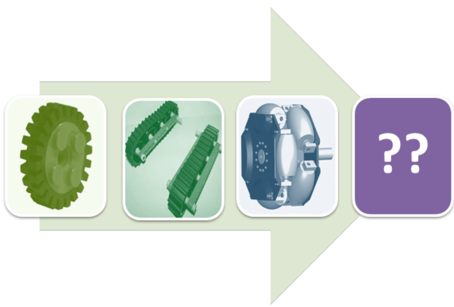
2. the wheels give little grip since the rollers have little surface contact overall,

3. omni wheels are a specialist product that have to be ordered from abroad at high cost, and

4. the shipping of the omni wheels would have taken fairly long..

With these disadvantages in mind, we felt that omni wheels were not the ideal solution for flexible movement.

Our Novel Wheel Design



After considering the wheel types used by previous robots we came up with a novel design we call the **turntable wheel**. Using a Lego turntable provided in our NXT kit, we could make a conventional static wheel which could be independently turned and powered to permit movement in any direction. The turntables allow for this by providing a movable platform with a central opening through which drive components could be fed from one side of the component to the other.

The turntable wheels can be seen as a fusion between the static wheels and *holonomic* wheels: the turntable wheels provide the conceptual simplicity and the levels of grip of the static wheels while also giving high levels of manoeuvrability as provided by the holonomic designs. We decided that the risk of using this untested technology was more than outweighed by the potential advantage this design could offer in terms of manoeuvrability while avoiding the grip issues, the complexity, and the costs associated with the holonomic wheels.

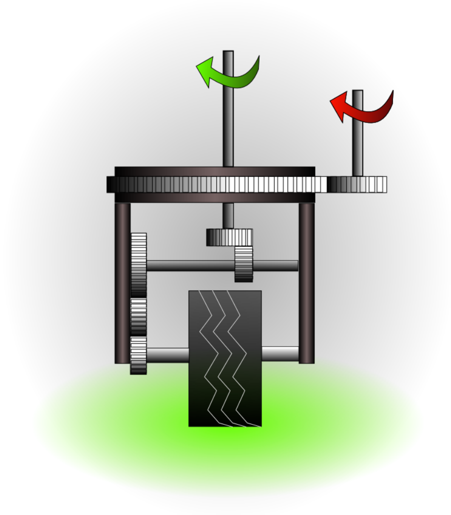


Figure 3: The turntable wheel

Chassis

Having decided on the turntable wheels, we created a chassis in which they could be effectively utilised. The chassis of our robot houses two turntable wheels placed in opposite corners with ball bearings on the remaining two corners to balance the robot.

In total, our design used 5 motors, 4 for the two turntable wheels, and an extra motor to power the robots kicker. Since the NXT control brick could only support 3 motors, it was necessary to use a motor multiplexer board to drive the extra motors.

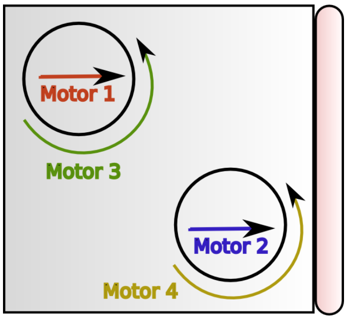


Figure 4: Chassis Design

Vision

The function of the vision system is to take as input the raw camera input and to produce as output the position of the ball as well as the position and the orientation or the bearing of the two robots on the pitch. The vision systems responsibilities are limited to what it can extract from a single image, disregarding any previous images. That is, the vision system is stateless, and can be considered to produce intermediate-level features from low-level features (the unprocessed camera input).

To add to conceptual clarity, and to minimise duplication of effort in creating high-level representations of the pitch state, we created an intermediary sub-system called the world to bridge the stateless vision system and the strategy systems together. Without this sub-system, each piece of strategy code would have potentially needed to implement their own ways to create the higher-level visual features. An added benefit of this split is that, irrespective of the strategy component used, each of the useful high-level features can be uniformly visualised with the vision GUI (and thus also eliminating any dependency between the strategy components and the GUI).

Our vision system implementation uses OpenCV with Python to achieve good performance and to be fairly flexible. Our complete system processes slightly more than 25 frames per second on the allocated DICE machines, beating the frame rate of the pitch camera.

The vision system is split into the following three logically distinct components:

Image acquisition: initially we used the native OpenCV methods for this, but eventually found that MPlayer worked better since some of the DICE machines started to mysteriously fail with the OpenCV methods.

Preprocessing: the frame is cropped and undistorted (though ultimately we disabled undistortion since we failed to get good camera calibration data).

Feature extraction: the objects in the image are recognised using a combination of thresholding and an iterative method for estimating the orientation. We spent tons of time trying to get this right and finally succeeded in making the vision system very robust and capable of detecting the objects in virtually all situations where it mattered.

Feature extraction explained

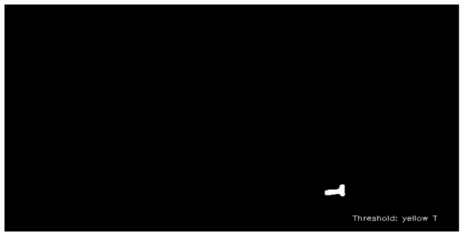
After trying out a lot of different methods, we finally managed to reduce the vision system to a simple core that performs very well under virtually all real-world match situations. The resulting vision system is perhaps deceptively simple in hindsight, but the problem is in finding the right simple methods for making it work.

A key aspect to our ultimately well-performing vision system is that the threshold calibration is very easy and fast to do with the system GUI (the threshold calibration sliders for each threshold can be toggled with a key press). Prior to doing this, we spent a lot of time manually adjusting the threshold constants in the code base, without too much success.

Our system uses thresholding as its basic filtering mechanism using well-calibrated thresholds, usually for each pitch separately (the lighting conditions vary considerably). There are four basic thresholds (ranges of colour values in the RGB or the HSV colour space), one for each of: the ball, the blue T, the yellow T, as well as the direction marker. Of these, the black direction marker is the most problematic (since it is nowhere near as dark as it looks), while the rest of the thresholds almost always give exclusively the right object and nothing else (see Figure 5 for the difference).

To be able to obtain the robots direction accurately, we found that the direction marker is virtually necessary; deriving the direction using the best-fitting bounding box of the T or the robots chassis can be wrong by up to 40. To get a better-quality thresholded image for the direction marker, we initially also included background subtraction in the preprocessing stage, but ultimately found that we could not make the background-subtracted intermediate image work in all the normal situations.

Our ultimate solution to the problem of finding the black direction marker involves using the shape of the thresholded T by finding the direction its top part is facing by finding its *central moment* (or its centre of gravity). Using the central moment and the centre of the bounding box of the thresholded T, we obtain the direction of the robot with relatively low accuracy (up to 40). We then proceed to refining this estimate by using bitwise AND over the pixels of the direction marker-thresholded image, using a circle-shaped bitmask of increasing radius that is centered near the expected location of the direction marker (a fixed distance towards the low-accuracy expected heading of the T). We iterate this process until we find the AND operation yields a result that is above a fixed number of pixels (we used 10 pixels for this). We find that this method is very accurate, though it sometimes gives wrong results near the pitch corners (where the correctness usually does not matter at all anyway).



(a) thresholding for the coloured T


(b) thresholding for the direction marker

Figure 5: The thresholded images

Robot control system

We programmed the physical robot system in Java, using a custom NXT firmware called Lejos. We chose Lejos without looking too much into alternatives as Lejos was easy to use and had a great library containing virtually all the functions we would need to make the NXT do anything.

Our initial design of the control system was made to be as stateless as possible, such that raw motor commands would be send and would remain in effect until a new command overrode them. This, we thought, would make the robot extremely responsive and capable of reacting to new circumstances immediately. Though we could send up to 50-70 commands per second second, we found that the camera latency (around 300-400 ms) would cause heavy oscillations since commands were based on outdated information and consequently the robot would almost always offshoot the target.

In hindsight, *visual servoing* could have possibly solved this problem almost perfectly, although the hidden states of the turntable wheels might have made it too complicated. However, we very much recommend teams with simpler designs to try out a visual servoing solution.

To cope with problematic direct motor commands, we migrated some of the commands previously used in the PC-side strategy code directly onto the robot. These commands included: straight-line movement along some bearing relative to the robot, as well as rotating the robot along its own axis by a specified angle. The migrated commands would execute on a longer timescale than with the previous command protocol (approx. 1 or 2 per second). With the control system, the commands would take a non-deterministic amount of time to execute, which, as we found out near the final match, would cause problems with large-scale oscillation related to ignoring most of the received commands and only executing the latest one.

Communication server

From the very start, one of the key requirements for our system was to have a reliable and robust connection with the robot. Since the robot control system being developed in Java using the Lejos library, we decided that using the corresponding computer-side communication classes would ensure a match up in protocols.

Since the rest of our system was written and Python, and in order to make the communications well-encapsulated part, we opted create a simple, stable socket server that would initialise a Bluetooth connection and keep it open as long as possible. The socket server would then act as a proxy for the strategy system to transmit commands. Since the communication server would keep the Bluetooth connection open regardless of the strategy code, we spent less time on resetting the robot and also gained the ability to switch between different strategies on the fly.

The first priority for us was to some basic bridge between the robot and the strategy system. After this was achieved, we focused on making the sub-system even more robust through the adding of reconnection features if a connection got closed for some reason, as well as more capable by adding the ability to receive incoming data from the robot (sensor inputs).

Strategy

At an architectural level, the strategy system is merely an interface used for handling abstracted robot commands as well as to receive abstracted vision information from the world module. In the default mode of operation, the world module would be hooked up to the vision system and the communication interface would point to the Bluetooth interface server, but, both were made abstract to permit hooking the code into simulated equivalents to allow for testing subsystems independently.

We built the strategy system in accordance to match our first communication protocol, such that each strategy module functions by taking in a world state and outputting a command based on that state alone, i.e. sending about 25 commands per second. Though the assumptions we used for deciding on this mode of operation had changed, we never really considered changing way the strategy system worked until it was too late.

Since the later robot command protocol executed only 1 or 2 commands per second, ignoring the rest, the new combined control system could exhibit much larger-scale oscillations where the robot would drive forward for far too long until a later command was received. These oscillations were caused by the robot ignoring most of the commands and only executing the ones that (sometimes) happened to correspond to more or less what it was doing anyway.

Though we never came up with a satisfactory solutions to these problems (in time!), should a future SDP team create a robot with design similar to ours, we strongly advise for designing the strategy/control system such that commands would get sent when deemed necessary (for major course changes), i.e. that there be some part that interprets what the system currently does, and decides whether a change would be beneficial, sending a move to the idle robot control system. However, this is a complex proposal where much could go wrong. Something simpler like visual servoing should be tried first. A third possibility would be to aggregate the commands and send the mean/median command (whatever that means).

Simulator

Early on we realised we would have many difficulties developing good ways to control our unconventionally designed robot. Until relatively late into the course, we would often have various problems with our physical robot: the design might not have been robust enough, some component was physically broken, the batteries were out of charge, etc., so we needed to have an alternate way to test at least some parts of our system without needing to use the costly robot. For this reason, and since our vision system wasnt very reliable until sometime near the first friendly match, we created a simulator that could accurately duplicate our robots physics, to visualise and otherwise test the performance of different strategies.

Reinforcement learning and artificial potential fields

Since we expected that the competition in SDP would be much harder this year, we looked out to see if we could further use some proven state-of-the-art techniques from actual Robocup tournaments. We found two promising candidates: *reinforcement learning* and *artificial potential fields*.

We implemented a basic reinforcement learner system using our simulator. The learner used an algorithm called *fitted value iteration* which would first explore various actions given a state of the robot relative to the ball, and always choose the one that yielded the best expected reward (defined by the reward function that would essentially reward kicking the ball correctly and penalise inaction or going the wrong way). Unfortunately, though the basic approach seemed sound, the performance of the learning system was far too low to yield usable results before the end of SDP (the system was written in Python/Numpy and further compiled using Cython). Though this failure falls under doing something too complicated in hindsight, we expect that reimplementing the reinforcement learner and its physics model in C would have yielded the speedups to make it work (the system would have needed to be a few orders of magnitude faster).

Artificial potential fields (APFs) have been widely used for many robot planning tasks. We realised that APFs, properly calibrated, would make a simple and attractive way to guide our early robot using direct motor control. APFs are computationally very cheap to use and compactly specify the direction a robot should move in: towards the ball in the right away, and around the opposing robot. Though we did get some promising results using APFs, especially in the simulator, ultimately we experienced similar problems as we had with the earlier direct motor control attempts: the robot would move in a jittery way, and since the robot could not, in general, move while turning, the speed of the robot would be greatly reduced. Another problem we had with APFs was that it was difficult to get the shape of the magnet-like directed potential field surrounding the ball to be exactly the right shape. In Figure , the field is shown to be slightly too wide than would seem optimal. Ultimately we replaced APF-based movement with straight line movement using virtual landmarks (as described below).

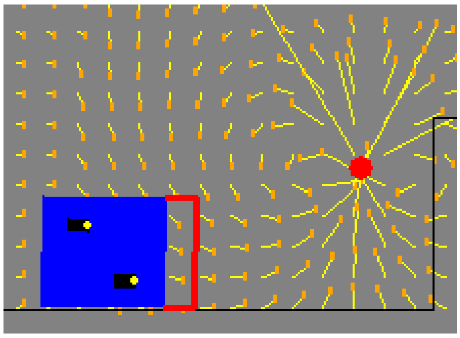


Figure 6: A visualisation of artificial potential fields in the simulator

Virtual landmark-based navigation

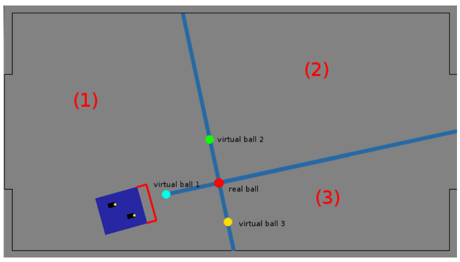


Figure 7: A visualisation of the landmark-based navigation method

This was the first method we evaluated for making the robot score goals. With this method, the robot navigates to virtual landmarks (or balls) rather than to the actual ball. The virtual balls are placed so as to assist the robot in kicking the ball behind it without first colliding with it. As can be seen, the landmarks are placed so as to point to the opponents goal. The strategy code for using this method then consists of three rules:

1. If the robot is between the ball and landmark 1, go to the ball.
2. If the robot is in area (1), move to landmark 1.
3. If the robot is in area (2) or (3), go towards and past the closest landmark.

Subsumption architecture and geometric movement planning

Our final strategy builds on all the previous ones and involves a somewhat sophisticated set of features used for directing the robot towards certain points of interest. The main feature of this strategy is the use of goal-target cone points. As seen in the following screenshots of our system GUI, we draw a circle of fixed distance around the ball and project on it points corresponding to the optimal kicking position for each player, as well as the corresponding bounds: if the robot is close the opponents goal, the bounds are loose, but otherwise the robot would have to be very precise its approach angle if it wanted to score a goal with just one kick. For more detail, see the world/strategy code (it should be fairly readable).

Ultimately, we implemented this strategy far too late and even had to disable parts of it while doing the final tests when we found certain parts of it to be broken or otherwise not behaving as expected. We ultimately managed to make the core logic into a linear sequence of if-then rules, classifying the combination of the robot and strategy as having whats called the *subsumption architecture*.

Below are the simplified rules for the implied subsumption architecture rule set (only the first matched rule is executed):

1. If the ball is far from me and the opponent is near the ball, go between the ball and my goal.
2. If the ball is far from me and the opponent is not near the ball, go towards the goal-kick point (the thick blue/yellow point on the circle matching the robot colour).
3. If my approach angle to the ball is within the bounds (smaller circles), go to the ball directly.
4. If I am not between the ball and my goal, go to the nearest tangent (the barely visible circles).
5. If the opponent is near the ball, go between the ball and my goal (play defensive).
6. If I am near the opponents goal (the ball is guaranteed to be near now), move to the goal-kick point.
7. If nothing else applies, go directly to the ball.

System GUI

We designed the system GUI to be minimalist and yet to show all relevant intermediate and high-level features on the screen by default, as well as providing keyboard controls for hiding everything. The system GUI is associated with the strategy and robot side/colour selector (not shown) which allows for picking any combination of the three on the fly. See Figure 8 for screenshots of our system GUI.

World

The function of the world is to take as input the positions and orientations of each object on the pitch from the vision sub-system and to produce as output various high-level features based on them. The high-level features coded in were created one by one when some strategy component was found to have use for them. Being true to the system architecture diagram, as shown in the system GUI above, the world is agnostic of the side of the robot, making the world subsystem well-encapsulated and simple to work

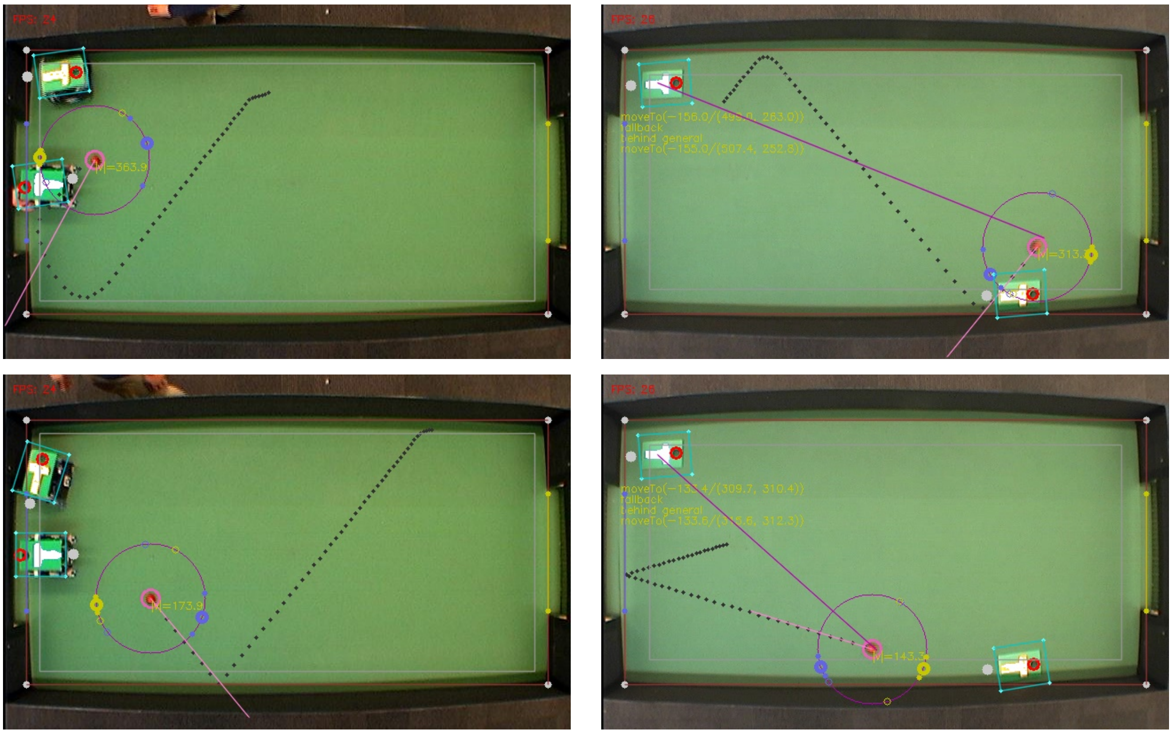


Figure 8: *Dont* handle special cases where possible; in this case, the apparent erroneous trajectory prediction adds robustness: the pitch geometry tends to produce similar effects, and the opposing robot might block the ball anyway. We get contingency-handling for free using the simplified trajectory.

with. The high-level features provided by the world subsystem include:

- Ball and robot velocity vectors
- The boundaries of the pitch and the positions of each goal
- Estimated ball trajectories indexed by time (up to 5 seconds into the future, in 100 ms increments)
- Goal-target cones for estimating when the ball would hit the goal if kicked
- Approximate bounding boxes of the robots for collision avoidance in the strategy code

Evaluation and future extensions

Our team came up with a unique design that no team had used before. The challenges were great and we were unfortunately unable to deliver in the final matches. However, with some refinement, we believe that the turntable wheels have the potential to be a winning design and so hope that any future SDP students who read our documentation can learn from our mistakes and get the best out of such an interesting design.

In the final match, our robot would take unexpectedly long to switch between different commands. This led to the sort of oscillating behaviour we described in the section dealing with the control system, and consequently our robot lost the match against a similarly low performance robot with 0-1 score.

Recommendations for component reuse

- We recommend using our vision system and the associated world module. Probably the only remaining enhancement for the vision system would be to add the correct camera calibration data to remove the barrel distortion. The world module requires some audit regarding the newest strategy-related features.

- The strategy system is somewhat dependent on the specific design of our robot and could be altered to send messages only when needed for minimum control latency. The implementation is a bit messy.

- The GUI is relatively elegant. Use our GUI if youre using our vision/world modules.

- The simulator is somewhat dependent on our robot design but might be useful as a base system.

- The robot control system is not too elegant so probably *dont* base your control system code on it.

Lessons for future work

In the course of developing our system, we discovered a number of important and general principles that helped or would have helped build our system, and that will most likely be useful for any future work:

- Simplicity is paramount: there are things you will *invariably* get wrong by assuming specific structure to the problem. You make progress much faster and get more feedback if you do the absolute simplest thing first. c.f. Galls law. **This is by far the most important thing and cannot be emphasised enough.**

- Ruthlessly throw away unnecessary code to make the system simpler. Your version control will keep track of anything you delete anyway so there is no point to keep code around just in case.

- Only optimise where it matters: our vision system gets just over 25 FPS on DICE machines, but the camera only gives 25 FPS anyway so there is no point in making it faster.

- Visualise as many processing stages as possible (especially for strategy and vision code): this makes bugs easy to spot and gives some intuitions about the problem.

- Program sub-systems and functions by explicitly handling *all cases* (even if some things *should not* happen with the current version, they might happen in some later one).

- Make extensive use of logging to understand the system and the problem better and to better debug things that cannot be visualised easily.

- Test using the complete system as often as possible. Simulators and unit tests are good for making sure no regressions occur but they wont duplicate all aspects of the system. This is another way of saying that *systems integration is one of the key challenges in SDP.*

- Give everyone actionable responsibilities. Keep track of the responsibilities by (for example) committing to publicly logging the time everyone has spent on SDP in group reports (applied game theory).

- Minimise time spent on meetings involving the whole group by using something like SCRUM (5-15 minutes max per meeting).

- You will commit the planning fallacy. You can mainly combat this by reducing the amount of work to be done by sticking to the bare minimum needed.

- Try to keep public development diaries so that everyone will know whats going on with other parts of the system if needed.