Shared Ball Estimation and Obstacle Detection for Robotic Soccer

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This summer, I helped prepare Bowdoin’s RoboCup team, the Northern Bites, for the world robotics competition in João Pessoa, Brazil. RoboCup is an international robotics event where teams compete in soccer matches, rescue missions, or home tasks. The Northern Bites compete in the Standard Platform League of robotic soccer, where our robots play autonomously in matches.

My portion of work dealt with determining a shared estimation of the ball’s location on the field through a shared ball module and calculating the location of various obstacles. Knowing the ball’s true location and being able to share that amongst the robots is especially important when a robot loses sight of the ball. With the correct information, it may continue with its intended play instead of wasting precious time searching for the ball. Additionally, without obstacle detection, a robot may receive a penalty for walking into another robot, or even become stuck in a position with a body part locked to the obstacle. Both accurate detection and avoidance of obstacles is crucial in the game, as we can’t risk losing any robot from the immediate gameplay because they are walking into an obstacle.

Each robot has its own estimation of where it is on the field and where it thinks the ball is. However, many times this information is incorrect, and it becomes difficult to determine the ball’s true location. In fact, very often robots will give very different estimations of the ball, so it is important to carefully select only the reliable estimates. My shared ball module takes in all ball estimates from the robots that see the ball and groups them by agreement. For two estimates to agree and be placed in the same grouping, they simply must have locations within a small distance of each other. Then, the module takes the grouping with the largest number of estimates and calculates a weighted average of the ball location, based each robot’s distance away from the ball. The closer the robot is to the ball, the higher the weight. If all groupings have the same number of contributions, the grouping with the goalie’s estimate is prioritized, as the goalie doesn’t move much in the game and is our most reliable player. If there is no tiebreaker, there is something very wrong with the robots’ estimates and we do not use the shared ball to make decisions in gameplay.

One of the more important aspects of calculating a shared ball estimate is being able to “unflip” robots. Since there are no distinct markings to separate the sides of the field, both appear identical to the robots. Therefore, it is very easy for a robot to flip his localization on the field, meaning his localization has been reflected through the center of the field, because the field looks exactly the same to the robot from either location. A flipped robot will kick and shoot towards the wrong goal, which can largely threaten how well we progress in a game. Once the shared ball estimate is determined, if any robot’s own ball estimate is in the same location as the shared ball reflected through center field, we say that robot is flipped and therefore reset his localization to the correct position: “unflipping.” To avoid incorrect unflipping, we don’t when either the shared ball or the robot’s ball estimate is in the center circle on the field.

Previously for obstacle detection, we used robot sonars and arm sensors, but the sonars have become somewhat unreliable, especially when detecting obstacles straight ahead. To replace the sonars, I introduced visual obstacle detection. Using buffers that are updated every image frame, with about 30 frames per second, I kept a record of the closest obstacle in each direction around the robot. If any obstacle distance drops within a given threshold around the robot, the robot躲避s the obstacle in a direction where there are no obstacles, and then continues on its previously intended path. This saves our robots from penalties for walking into other robots, and helps them approach the ball more efficiently.

With these additions to our code base, our robots were able to share a correct ball location, successfully unflip their teammates based on ball estimates, and improve how easily they navigated the field. There are many opportunities to expand upon these projects during the year, so I plan to develop a more reliable method of avoiding obstacles. It may be more reliable to combine sonars, arm sensors, and vision together for improved accuracy, along with updated sonar function. Unnecessary avoidance of obstacles can be just as dangerous as not avoiding at all, so it is important to test our methods further and perfect these proposed solutions.

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