BabyTigers 2003: Osaka Legged Robot Team

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1 Introduction

We are interested in learning issues such as action selection, observation strategy without 3D-reconstruction [1–3], emergence of walking, and cooperative behaviors. Basic implementations, such as vision, actions, and walking, are mostly derived from our previous work [4] and the actions and walking of the United Team of Kyushu (part of their work was based on the University of New South Wales one). Then we briefly describe our current work in cooperative behaviors in this paper.

In a multi robot system, it is expected that communications or information sharing between robots help acquiring the knowledge about their environment. When multi robots communicate with each other, they seem to need a reference coordinate system to exchange their information about the environment. In case of mobile robots, the world coordinate or the coordinate fixed to the environment are often used. To convert the observation to the world coordinate, each robot localizes itself. Assuming that localization errors are small or neglectable, information exchange between robots have no problem. However, localization errors often become too large to ignore.

Methods to localize itself and to acquire knowledge about environment by shared information from other robots are proposed [5, 6]. They use geometric constraints between several robots which are commonly observed from each other, calculates their positions, and share the environment map. The errors of self-locations are minimized so that shared observations conform to geometric constraints. To observe several robots at one time, they used omni-directional cameras rather than normal cameras with limited view angles. However, in case of robots with the latter cameras, there will be many situations that they will not be able to observe others. Then it becomes difficult to use such methods.

Although the representation of self-location by probabilistic form and use of beliefs are proposed and commonly used in order to handle the error of self-localization, it is difficult to obtain the accurate model to merge the maps by two or more robots and to maintain the shared map. Simple weighted average of information by robots may work when the errors are small. However when one of the robots has a large error on its self-localization it will affect the shared map used by all other robots. Designing weights or accuracy measurements to prevent such a case is difficult because there are always errors that is unknown to the designer and in many situations errors are not detectable by the robot itself. Then, we propose a subjective map based approach rather than shared map based one. A subjective map is for a multi-agent system to make decisions in a dynamic, hostile environment. It is maintained by each robot regardless of the objective consistency of representations among other agents. Owing to its subjectivity, the method is not affected by other agent's information which may include not negligible errors due to dynamic changes in the environment caused by accidents. A potential field is defined on the subjective map in terms of subtasks such as ball reaching and shooting, and is dynamically updated to make a decision to act.

2 A subjective map generation

Let us assume that there are two robots (robot A and robot B) and one object (a ball) in an environment. These robots have localized themselves and they are watching at the ball but they cannot observe each other due to their limited view angles (Fig.1). If we ignore the localization errors and put information on a map, there will be contradiction about the ball position as shown in Fig.2(a).

If we use the weighted average of the ball location $\hat{\boldsymbol{x}}$,

$$\hat{\boldsymbol{x}} = \frac{{}^{B}\sigma {}^{A}\boldsymbol{x} + {}^{A}\sigma {}^{A}\boldsymbol{x}}{{}^{A}\sigma + {}^{B}\sigma}, \tag{1}$$

where ${}^{A}\boldsymbol{x}$, ${}^{B}\boldsymbol{x}$, ${}^{A}\sigma$, ${}^{B}\sigma$ are the ball positions and their deviations estimated by robots A and B, respectively, assuming Gaussian distributions. Then we have a map shown in Fig.2(b). There is no contradiction in this map. However, this is not the true ball position in the world coordinate system. When robot A has correct estimation while robot B has incorrect one, robot A's estimation become worse because of the information sharing. Also there are cases the relative position to the robot itself is more important than the absolute position in the world coordinate system. Further, it becomes more complex when the robots can observe each other. If we can assume the simultaneous observations from several robots are available then we could use geometrical constraints and reduce errors [5, 6]. In case of robots with limited view angle cameras and they are moving, we cannot assume it.

Here, we propose that each robot constructs its subjective map and determines its action based on it. For example, robot A believes its observation for the ball and calculate position of robot B from the relative position between the ball and robot B as,

$$\hat{{}^{A}\boldsymbol{x}_A} = {}^{A}\boldsymbol{x}_A, \tag{2}$$

$$\hat{{}^{A}\boldsymbol{x}_Q} = {}^{A}\boldsymbol{x}_{ball}, \tag{3}$$

$$\hat{{}^{A}\boldsymbol{x}_B} = {}^{B}\boldsymbol{x}_B + ({}^{A}\boldsymbol{x}_{ball} -{}^{B} \boldsymbol{x}_{ball}). \tag{4}$$

Fig.3 shows the subjective maps of robots A and B. With these subjective maps, although reduction of localization error is not achieved, robot A is not affected

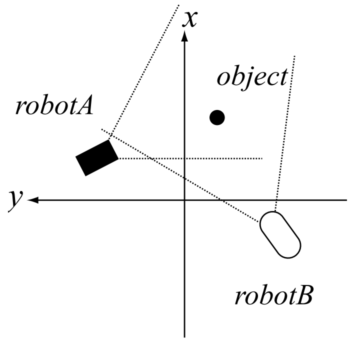


Fig. 1. There are two robots watching at a ball.

by the localization error of robot B and can use the information from robot B. The subjective map method is expected to work for such a task and the environment that the relative positions is important rather than absolute ones, localization errors sometimes become large, and geometrical constraints are hard to use. In the following experiments, we compare the action decisions by shared map with average position method and decisions by subjective maps in a robot soccer environment with four legged robots. Robots determine their actions from potential field calculated from a shared or its subjective map.

3 A potential field for making decisions

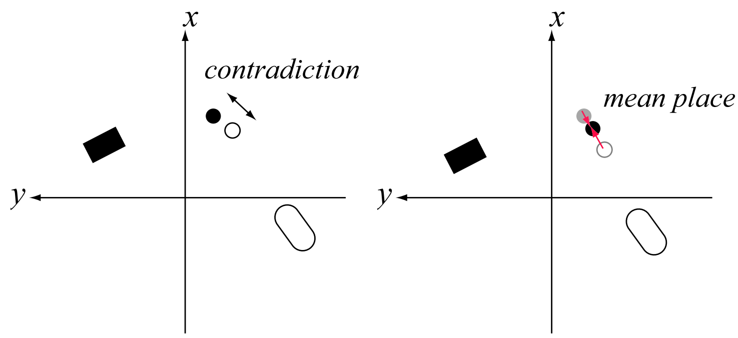
We define a potential field which depends on a subjective map of a robot. Each robot calculates the field from the map and determine its action according to the field. A robot has four actions, move forward, turn left, turn right and shoot a ball. It takes such an action that climbs the potential field if the ball is far and shoot it to the opponent goal as it approaches close.

The potential field $V(x,y)$ of robot i consists of three potentials. One is V_F which is the function of the position of a teammate j, ${}^i\boldsymbol{P}_j = ({}^i x_{R_j}, {}^i y_{R_j})$. The second is V_O which is the function of the position of an opponent k, ${}^i\boldsymbol{R}_k = ({}^i x_k, {}^i y_k)$. The last one is V_B which is the function of the ball position ${}^i\boldsymbol{Q} = ({}^i x_Q, {}^i y_Q)$. All the positions are derived from its subjective map. In the following, we give example potentials based on the setup shown in Fig.4.

Potentials by a teammate V_F and opponent V_O are calculated by,

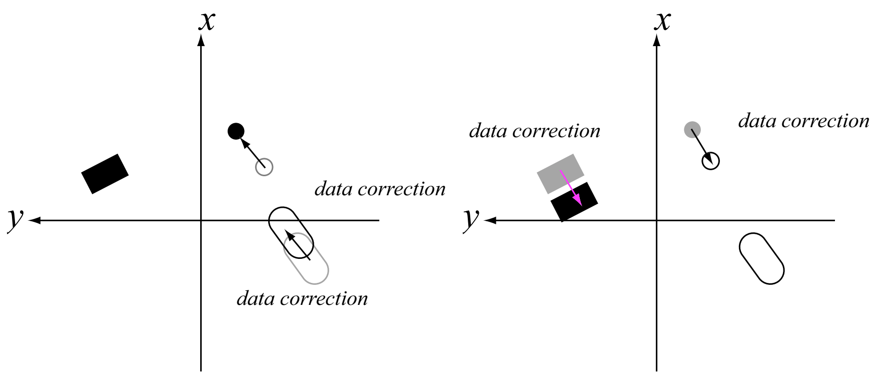
$$V_F(x,y) = -\sum_{j(j\neq i)} f({}^i\boldsymbol{P}_j), \tag{5}$$

$$V_O(x,y) = -\sum_{k} f({}^i\boldsymbol{R}_k), \tag{6}$$



(a) with assumption of no localization error (b) with averaged locations

Fig. 2. Constructed map with assumption of no localization error and with averaged locations



(a) the subjective map of robot A (b) the subjective map of robot B

Fig. 3. The subjective map of robot A and robot B.

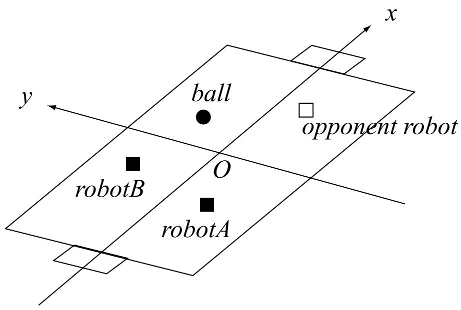
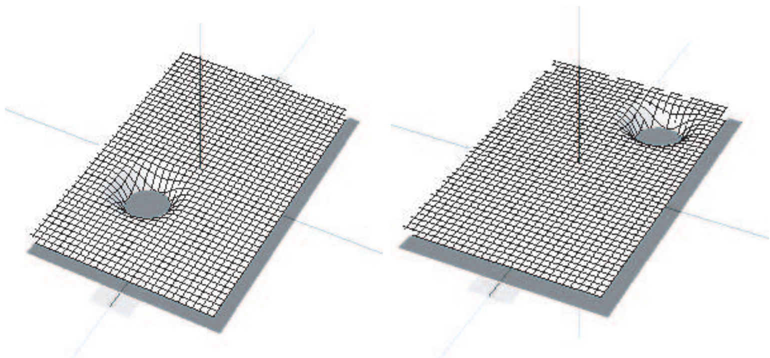


Fig. 4. True object locations



(a) V_F of robot A (b) V_O of robot A

Fig. 5. Potential diagram V_F and V_O of robot A.

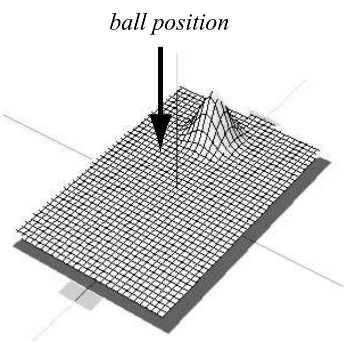
where,

$$f(\boldsymbol{P}(\bar{x}, \bar{y}, \sigma_x, \sigma_y)) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\cdot\left(\left(\frac{x-\bar{x}}{\sigma_x}\right)^2+\left(\frac{y-\bar{y}}{\sigma_y}\right)^2\right)}. \tag{7}$$

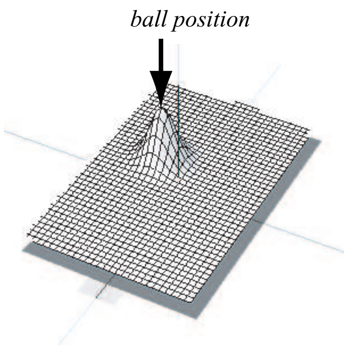
These potentials are to avoid robots in the field. Fig.5 shows the V_F and V_O of robot A in the example setup.

The potential from the ball is defined so that the robot closer to the ball will reach ball, others will go to the position where it can back up the shoot. The potential function of robot i is switched depending on if i is the closest to the ball or not,

$$V_B(x, y) = \begin{cases} f({}^i\boldsymbol{Q}) & (\textit{robot } i \textit{ is the closest to the ball}), \\ f({}^i\boldsymbol{Q}') & (\textit{otherwise}), \end{cases} \tag{8}$$



(a) V_B of robot A, it is highest at support position



(b) V_B of robot B, it is highest on the ball

Fig. 6. Potentials from the ball (V_B)

where ${}^i\boldsymbol{Q}$ is the position of the ball, and ${}^i\boldsymbol{Q}'$ is the support position. ${}^i\boldsymbol{Q}'$ is defined as,

$$ {}^i\boldsymbol{Q}' = \frac{1}{2}\left({}^i\boldsymbol{Q} + \boldsymbol{G}\right), \tag{9} $$

where $\boldsymbol{G}$ is the position of target goal. The example potentials of robots A and B are shown in Fig.6. Final potential fields are shown in Fig.7.

We have been experimenting this approach with the robots and the field for RoboCup SONY Legged Robot League 2002. Our current self-localization program for the experiments is based on Carnegie Melon University's CM-Pack'01 [7]. Its approach is a Kalman-filter based self location tracking with multi hypothesis which start from different points in the field. Experimental results will be presented in elsewhere.

Acknowledgment

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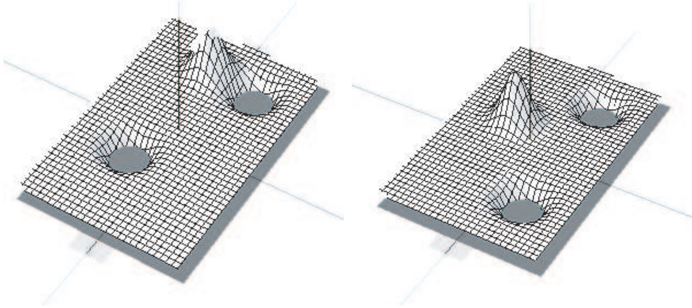

(a) robot A (b) robot B

Fig. 7. Final potential fields of robots

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