

Multiple Self-Organizing Maps for Visuo-Motor System that uses multiple cameras with different field of views

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Abstract: This paper proposes multiple self-organizing maps (SOMs) for control of a visuo-motor system that consists of a redundant manipulator and multiple cameras in an unstructured environment. The maps control the manipulator so that it reaches its end-effector to targets given in the camera images. Also the maps make the manipulator take obstacle free poses. Multiple cameras are introduced to avoid occlusions and multiple SOMs are introduced to deal with multiple camera images. Simulation results will be shown.

Keywords: Robot vision systems, Self-organizing maps.

I. INTRODUCTION

Vision guide for a manipulator has been one of the major research issues in robotics. Coordination schemes of visuo-motor systems can be classified on the basis of the knowledge about manipulator kinematics and camera parameters. Many researchers have proposed a number of systems that deal with unknown manipulator kinematics and unknown camera parameters. In the studies, visuo-motor models are either estimated analytically during the execution of tasks on-line or learned prior to the execution off-line. Artificial neural networks can be used to learn the non-linear relationships between features in images and the manipulator joint angles. Miller et al. proposed a neural network based on the learning control system, where a cerebellar model arithmetic computer memory was employed for the learning [1]. Carusone et al. used a network to train an un-calibrated industrial robot [2]. In their systems, neural networks provided the estimation of the poses of targets in the manipulator coordinate frames, and the poses were used to guide the manipulator to grasp the objects. However, supervisors were needed in the systems.

Self-organizing map (SOM) based on the Kohonen algorithm is an important unsupervised artificial neural network model [3]. It has shown great potential in application fields such as motor control, pattern recognition, optimization, and so on, and also has provided insights into how mammalian brains are organized [4] [5]. During the past years it has been

demonstrated that the SOM can solve the inverse kinematics problem for visuo-motor control. Buessler et al. determined arm movements by tracking an image target [6] [7]. The correlation between an image-defined error and the joint movement was learned on-line using self-organizing algorithm for making the error zero. Multiple neural maps were combined to simplify neural learning in their study. Martinetz et al. and Walter et al. used a three dimensional lattice to learn the nonlinear transformation that specifies the joint angles of a 3-DOF manipulator so that the angles take the tip of the manipulator to a target point given in the coordinates provided by two cameras [8] [9]. In all of these studies, however, they solved the visuo-motor coordination problems with non-redundant manipulators in an environment without obstacles. Such obstacle avoidance problems are important for manipulators that work in real environments. Zeller et al. developed a motion planning for a non-redundant manipulator to avoid collision with obstacles in a cluttered environment by using the TRN model [10]. They used a fact that a locally optimized path can be determined by minimizing the Euclidean distance from the current position to a given goal. Collision check was performed not in the self-organizing process but in the path planning process afterwards. In contrast to these precedent studies, our system is not only for precise positioning of the end-effector but also for ensuring obstacle free poses of the manipulator. We intend to realize coordination for a visuo-motor system with a redundant manipulator in a cluttered environment. The redundancy is then used to

make the manipulator take obstacle free poses and achieve high manipulability.

In the previous researches, Zha et al. used a SOM to coordinate a visuo-motor system in an environment with obstacles [11]. Collisions between the links and obstacles were, however, not well considered. We introduced a potential field to avoid such collisions only in a 2D space [12]. Han et al. realized collision avoidance for a visuo-motor system in a 3D space [13]. The occlusion problem was, however, not solved effectively even in the system.

Vision systems are generally classified by the number of cameras, camera configurations, the level of calibration and some a priori knowledge about the scene. The binocular configuration is a commonly used configuration. In comparison with the eye-in-hand configuration, it allows a wide field of view and then it makes easy to observe both the manipulator and targets simultaneously. Such a vision system was employed in [13]. However, since they treated spaces occluded by obstacles in the image space as unreachable spaces for the manipulator, the workspace was restricted.

In order to handle the occlusion problem, we have developed a visuo-motor system with multiple related SOMs and a redundant camera system in this paper. The SOMs are directly connected to the cameras and learn to perform manipulator control. Based on the visibility of a target given in the workspace, the appropriate map is selected. The map outputs a joint angle vector which makes the manipulator reach the target with an obstacle free pose. The proposed learning algorithm ensures that the manipulator moves smoothly and consistently in the whole workspace no matter which map is selected. The advantages of the proposed method are: (1) By employing multiple maps, the system overcomes the occlusion problems in cluttered environments. The cooperation and complementation of maps make the manipulator consistently move in the whole workspace. (2) In our self-organizing learning procedure, the visuo-motor system learns not only to position the end-effector precisely but also ensure that the manipulator takes obstacle free poses.

This paper is organized as follows. First, an outline of our visuo-motor system is introduced in the section II. Introduction of a near camera is discussed in the section III. Simulation results are shown in the section IV. Finally, conclusions are given in the section V.

II. OUR VISUO-MOTOR SYSTEM

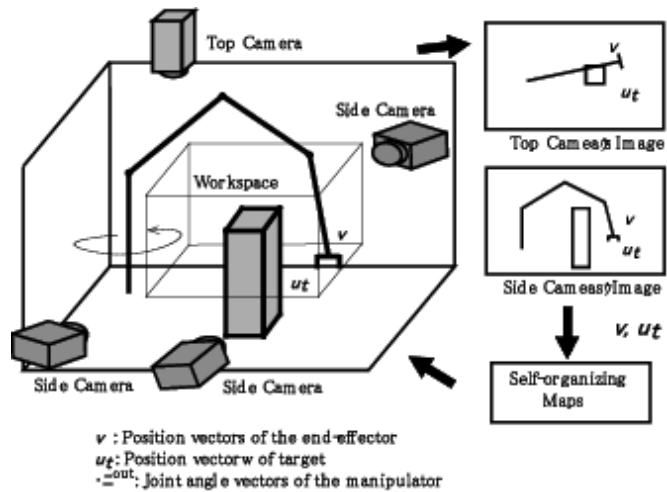


Fig.1. Outline of our visuo-motor system.

Our visuo-motor system is illustrated in Fig.1. The system contains a 4-DOF redundant manipulator, multiple CCD cameras, and multiple related SOMs. The CCD cameras are used to get the target positions, the locations of the end-effector and the manipulator poses. They also acquire information about obstacles by simple using threshold. From visual information provided by the cameras, the SOMs learn projections that convert the position vectors of the targets in the image spaces into the joint angle vectors of the manipulator.

Although stereo camera systems can provide 3D information and we have used such a system in our previous works [12] [13], the system could not well deal with spaces occluded by obstacles. They introduced 3-cameras system to overcome the situation [14]. However, the result was limited. To deal with the occlusion problem, a multiple camera system is presented in this paper. The valid workspace is extended by using the cameras at multiple viewpoints. Related SOMs are simultaneously employed in the visuo-motor system. For the detail of the algorithm using in our system, please refer to our previous study [14].

III. INTRODUCTION OF A NEAR CAMERA

We added a near camera in our system to reduce the positioning error as shown as in Fig.2. This camera has a narrow view than other cameras. And it can only

obtain the image coordinates of the neurons that enter given categories.

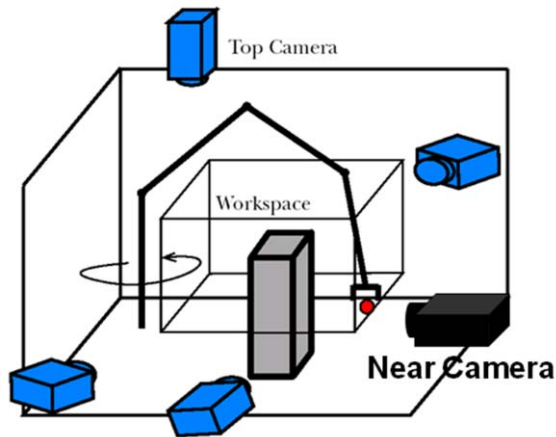


Fig.2. Outline of our visuo-motor system with a near camera

The near camera's SOM has a different learning algorithm from others. First neurons which are generated without the near camera are divided into two groups according to whether the neuron position can be seen by the near camera. The group of the neurons with positions which can be caught in the near camera does the self-organizing maps' learning procedure by using the data from the near camera and updates the neurons' parameters again. On the other hand, the other group of the neurons is left just as it is. The grouping is done for each target. Thus if the target position is in the given categories, by using the near camera we can get the more accurate pose of the manipulator.

IV. SIMULATION RESULTS

We have constructed an experimental system. By simulation and experiments, we have also revealed that a visuo-motor system with 3 CCD cameras and 2 SOMs can control a redundant manipulator and realize collision avoidance in an environment with obstacles.

In this paper, we aim at a system with 5 CCD cameras, 3 SOMs and a 4-DOF redundant manipulator, and show its validity by simulation. The cameras are assumed to be orthographic models and each camera has 640X480 pixel resolution. The simulation model is illustrated in Fig. 3. The length of each link is 120, 135, 110 and 140 pixels in the image spaces. Each SOM involves 240 neurons. 15000 targets were given in the learning process and they were distributed 200X200 pixels with a focus on the obstacle. The time required

Table 1. The average positioning error of the end-effector

| | Path 1 | Path 2 | Path 3 | Path 4 |
|-----------------------|--------|--------|--------|--------|
| Without a near camera | 2.91 | 2.65 | 2.90 | 3.35 |
| With a near camera | 2.18 | 1.84 | 4.37 | 2.64 |

for the learning was about 10 minutes using a PC with 3.0GHz Pentium4.

After the learning, the path planning system planned a collision-free path of the end-effector in the top camera image using Laplace potential method, and determined the shortest path in another camera image. Then the planning system divided the path into 34 positions and the SOMs outputted the collision-free poses for the positions. An example of path planning is shown in Fig.4. The average positioning errors of the end-effector for different path are shown in Table 1. And by Fig.5, we can see that the positioning errors of the

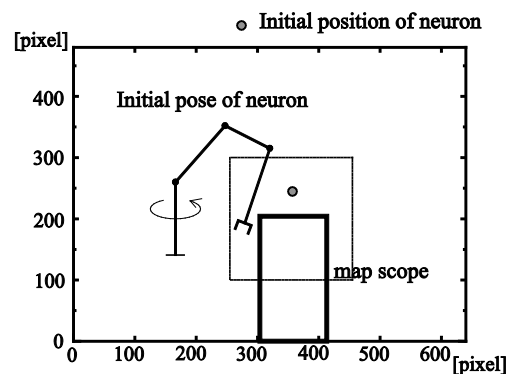


Fig.3. Assumed simulation environment illustrated in the image space of the right camera

end-effector don't change when the manipulator's pose is outside the view of the near camera, but once the target position enters the view of the near camera, the positioning errors are made smaller. In most situations, the average positioning error becomes fewer. However the average positioning error of path 3 becomes larger, we think the reason may be that the neurons are not filled enough in the view of the near camera. Now we are still dealing with that.

V. CONCLUSIONS

We developed a visuo-motor system with multiple self-organizing maps. The system consists of a redundant manipulator, multiple cameras and multiple SOMs corresponding to the cameras. By using the cameras, the system can control the manipulator in an environment with obstacles. To reduce the positioning

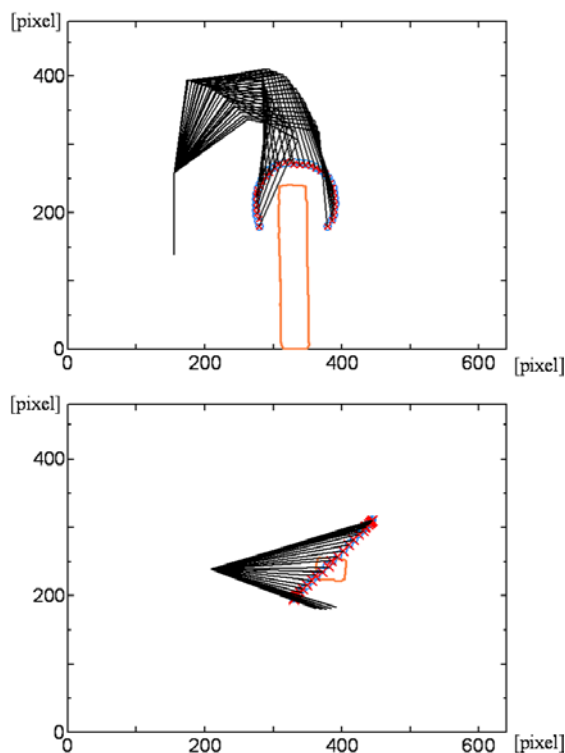


Fig.4. Collision avoidance by the simulation

error of the end-effector, we then added a near camera in our former system. Simulation results showed that by using the near camera we can get the more accurate pose of the manipulator in most situations.

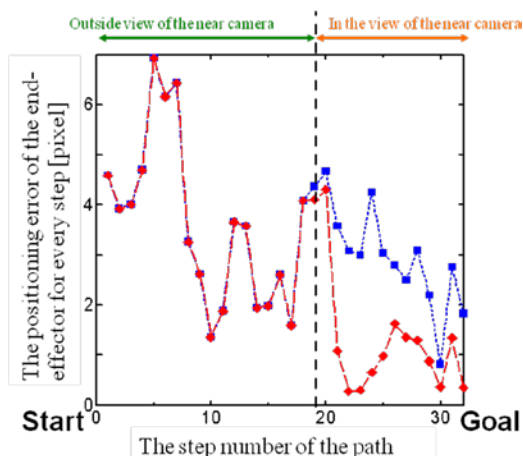


Fig.5. The path 4's positioning error of the end-effector for every step. (The dotted line: without a near camera; the dash line: with a near camera)

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