Dynamic DOF assignment through Interaction with Environment

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Abstract

To control a robot that has many degrees of freedom and various sensors, a method to dynamically assign the degrees for a task is proposed. First, a mechanism to estimate the relation between the sensor inputs and the control outputs is derived based on the least-mean-square method. Then, by observing the information matrix of the estimator, a method to find robot's redundancy with respect to a given task is derived. Applying the proposed scheme to the visual servoing task of a manipulator, we show several experimental results demonstrating that the method can find redundancy automatically, and can assign the redundant degrees to another task.

1 Introduction

To build up a really intelligent robot, a number of degrees of freedom and sensors are needed. They will provide adaptability and robustness to the robot. The more degrees and the more sensors the robot has, the more variety of tasks it is expected to accomplish. The numbers also concern to robustness against malfunction. If the robot has redundant degrees of freedom with respect to a given task, it can manage to accomplish the task even if several motors do not work.

The most popular method to deal with many actuators and sensors is the one based on so called a *sensor fusion* scheme: (1) building a world model base on *a priori* knowledge, (2) translating the given task into this model, (3) fusing data from various sensors on the model, (4) determining the behavior of the robot, and (5) deriving outputs to actuators to achieve this behavior. In this method, the designer must make a world model based on one's *a priori* knowledge, which makes the resultant system week against disturbances and modeling errors. The robot can deal with the environmental changes as far as they are described in the world model beforehand, but it cannot adapt itself to these changes that have not been described. Also, the robot cannot deal with malfunction of several actuators unless it is described beforehand.

If the robot has ability to dynamically assign its degrees to given tasks, it will be able to deal with such many degrees. When the robot is redundant with respect to the task, it can find the redundancy automatically and assign it to another task. In case several actuators do not work, it will assign others to the task dynamically. Since it will assign the degrees through its interaction with the environment, it can handle dynamic changes of the environment. A controller for a task cannot be designed without considering the environmental effect since the combination of the robot and the environment determines the overall behavior of the robot. The robot can learn its behavior only through the interaction with its environment. Therefore, if one wants to make an adaptive robot, it is crucial characteristic for the robot to obtain the relation between it and the environment, and to dynamically assign the degrees to the task.

There has been a certain amount of work trying to make an adaptive robot. In the field of control theory, they have developed adaptive control schemes which can estimate parameters but cannot find redundancy [1], [2]. There are also several attempts to make an adaptive robot by a control architecture such as a subsumption architecture [3] and a schema system [4], each of which also cannot utilize redundancy of the robot effectively.

In this paper, an adaptive controller is proposed that can find robot's redundancy automatically. The remainder of this article is organized as follows. First, a mechanism to estimate the relation between the sensor inputs and the control outputs is derived based on the least-mean-square method. Then, by singular value decomposition of the information matrix, a method to find the redundancy with respect to the given task is proposed. By this method, the robot can assign its degrees of freedom dynamically to the task, and assign redundant degrees to another task. Finally, applying the proposed scheme to a visual servoing task, experimental results are shown to demonstrate its effectiveness.

2 Servoing controller with dynamic DOF assignment

2.1 Jacobian matrix estimation based on least-mean-square method

Let $\boldsymbol{x}$ denote a sensor input vector, typically an external sensor vector like vision coordinate vector or force reading vector. If the robot does not have a global world model, the task should be given in its sensor space. Let the task be given as a desired vector $\boldsymbol{x}_d$ in the sensor space. The sensor input $\boldsymbol{x}$ is a function of actuator displacement $\boldsymbol{\theta}$:

$$\boldsymbol{x} = \boldsymbol{x}(\boldsymbol{\theta}). \tag{1}$$

Differentiating eq.(1), we can obtain

$$\Delta\ \boldsymbol{x} = \boldsymbol{J}\Delta\boldsymbol{\theta}, \tag{2}$$

where $\boldsymbol{J}$ denotes a Jacobian matrix that describes the relation between $\boldsymbol{x}$ and $\boldsymbol{\theta}$. To calculate the control output according to the error between $\boldsymbol{x}$ and its desired value $\boldsymbol{x}_d$, the Jacobian matrix $\boldsymbol{J}$ must be known. The estimated Jacobian matrix $\widehat{\boldsymbol{J}}(i)$ in i-th step satisfys the following equation according to the least-mean-square method formulation:

$$\boldsymbol{M}(i)\widehat{\boldsymbol{J}}(i)^T = \boldsymbol{Y}(i), \tag{3}$$

where

$$\begin{aligned} \boldsymbol{M}(i) &= \left[\sum_{k=1}^{i} \rho^{i-k}\Delta\boldsymbol{\theta}(k)\Delta\boldsymbol{\theta}(k)^T\right], \\ \boldsymbol{Y}(i) &= \left[\sum_{k=1}^{i} \rho^{i-k}\Delta\boldsymbol{\theta}(k)\Delta\boldsymbol{x}(k)^T\right], \end{aligned}$$

and $0 < \rho \leq 1$ is a forgetting factor. By applying the inverse of $\boldsymbol{M}(i)$ to both sides of eq.(3), we can get the estimated $\widehat{\boldsymbol{J}}$ as far as $\boldsymbol{M}(i)$ is not singular.

At the beginning of the control period, $\boldsymbol{M}(0)$ is a zero matrix according to this formulation, which makes the estimator unstable. By rewriting these equations in a recursive manner, we can get

$$\begin{aligned} \boldsymbol{M}(i) &= \rho\boldsymbol{M}(i-1) + \Delta\boldsymbol{\theta}(i)\Delta\boldsymbol{\theta}(i)^T, \\ \boldsymbol{Y}(i) &= \rho\boldsymbol{Y}(i-1) + \Delta\boldsymbol{\theta}(i)\Delta\boldsymbol{x}(i)^T. \end{aligned}$$

By giving arbitrary full-rank matrices for $\boldsymbol{M}(0)$ and $\boldsymbol{Y}(0)$, the robot considers that all the degrees of freedom are needed to achieve the given task at the beginning of the control period. Over time the robot will find its redundancy by the following DOF assignment scheme.

2.2 Dynamic DOF assignment

The matrix $\boldsymbol{M}(i)$ is so called an *information matrix* that describes the variation of $\Delta\boldsymbol{\theta}$. Let the singular value decomposition of $\boldsymbol{M}(i)$ be

$$\boldsymbol{M}(i) = \boldsymbol{V}\boldsymbol{\Sigma}\boldsymbol{V}^T, \tag{4}$$

where

$$\boldsymbol{\Sigma} = \mathrm{diag}\left[\sigma_1, \sigma_2, \cdots, \sigma_n\right], \qquad (\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_n),$$

and $\boldsymbol{V}$ is an orthogonal matrix. If the robot has redundant degrees with respect to the given task, $\boldsymbol{M}(i)$ becomes singular, that is, σ_n becomes very small, and therefore, the numerical calculation becomes unstable(the inverse matrix of $\boldsymbol{M}(i)$ will be very large). To avoid this instability, small σs must be explicitly eliminated from the estimation equation (3). When the condition number σ_n/σ_1 becomes small enough, say less than a threshold *varepsilon*, the robot will eliminate the corresponding orthogonal vector $\boldsymbol{v}_n$ from from eq.(3):

$$\begin{aligned} &\boldsymbol{V}\mathrm{diag}\left[\sigma_1, \sigma_2, \cdots, \sigma_{n-1}, 0\right]\boldsymbol{V}^T\widehat{\boldsymbol{J}}(i)^T \\ &\quad = \left(\boldsymbol{I}_n - \boldsymbol{v}_n{\boldsymbol{v}_n}^T\right)\boldsymbol{Y}(i), \end{aligned} \tag{5}$$

where $\boldsymbol{I}_n$ is an identical matrix. Then, the estimated $\widehat{\boldsymbol{J}}(i)$ becomes

$$\begin{aligned} \widehat{\boldsymbol{J}}(i)^T = \boldsymbol{V}\mathrm{diag}\left[1/\sigma_1, 1/\sigma_2, \cdots, 1/\sigma_{n-1}, 0\right]\boldsymbol{V}^T \\ \left(\boldsymbol{I}_n - \boldsymbol{v}_n{\boldsymbol{v}_n}^T\right)\boldsymbol{Y}(i). \end{aligned} \tag{6}$$

2.3 Servoing controller

Depending on the estimated Jacobian matrix $\widehat{\boldsymbol{J}}(i)$, a servoing controller can be derived,

$$\boldsymbol{u} = \widehat{\boldsymbol{J}}^+\boldsymbol{K}_p(\boldsymbol{x}_d - \boldsymbol{x}) + (\boldsymbol{I} - \widehat{\boldsymbol{J}}^+\widehat{\boldsymbol{J}})\boldsymbol{k}, \tag{7}$$

where $\widehat{\boldsymbol{J}}^+$, $\boldsymbol{K}_p$, $\boldsymbol{I}$ and $\boldsymbol{k}$ denote the pseudo-inverse matrix of $\widehat{\boldsymbol{J}}$, a feedback gain matrix, an identical matrix, and an arbitrary vector that denotes the redundancy, respectively. If the robot has redundant degrees with respect to the task, the small singular value of the information matrix is explicitly eliminated by the dynamic DOF assignment scheme, and then the estimated matrix $\widehat{\boldsymbol{J}}$ is rank deficient. Therefore the second term of right-hand side is not zero, and we can utilize the redundancy for another task.

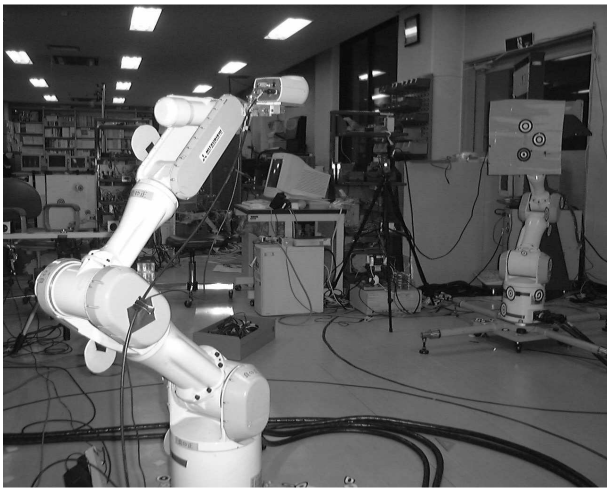

Figure 1: An overview of the robot system used for the experiment: The task for the robot is to keep the image view constant following the movement of another robot carrying the visual target.

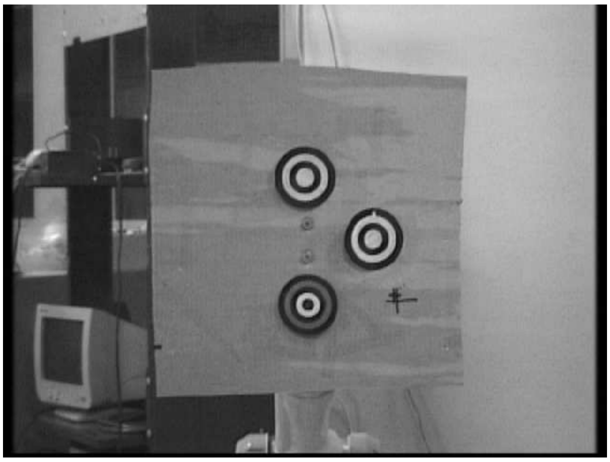

Figure 2: An image taken by the camera of the robot: Its task is to keep the image coordinates of these targets constant.

3 Experiment: Visual servoing task

Experimental results are shown by applying the proposed scheme to a visual servoing task to demonstrate its effectiveness. As is applied for visual servoing, the sensor input $\boldsymbol{x}$ consists of visual coordinates, and the task it to make this vector converge to the desired one $\boldsymbol{x}_d$.

3.1 Experimental setup

In figure 1, an overview of the robot system used for the experiment is shown. We use a 7 degree-of-freedom manipulator PA–10 (Mitsubishi Heavy Industry Co.) as a 6 degree-of-freedom manipulator, fixing joint 3 constant. it has a CCD camera to observe the visual target moved by another robot. The task for the robot is to keep the image constant, that is, the desired vector $\boldsymbol{x}_d$ is the one observed at the initial posture.

Video signals from the CCD camera are sent via a tracking module equipped with a high-speed correlation processor by Fujitsu (image size : 512[pixel] $\times$ 512[pixel]). We specify a certain region in the image (called a template) to be tracked before starting an experiment. During the experiments the module feeds coordinates, where the correlation measure (it uses a SAD measure, Sum of Absolute Difference) is the smallest with respect to the template, to the control computer (Pentium III, 500MHz). The computer calculates control signals for the manipulator by the proposed scheme and sends them to the manipulator controller via network(5Mbps). Using this experimental equipment and programs in C language on VxWorks (Wind River), the sampling rate of the visual servoing is 33[ms].

3.2 Experimental result:Applying proposed scheme

The target is moved in a diamond shape by another robot. An observed image is shown in figure 2.

As the second task for the robot, we applied a simple servoing task for joint θ_4:

$$\theta_{4d} = \pi/2.$$

The forgetting factor ρ is 0.998 and, the threshold ε for the condition number σ_n/σ_1 to determine the redundancy is 0.05 in this experiment.

In figures 3 and 4, experimental results are shown. In figure 3, the angle of joint 4 is shown with the condition number. As the initial value of the information matrix $\boldsymbol{M}(0)$ and $\boldsymbol{Y}(0)$, an identical matrix and an arbitrary full-rank matrix were used, respectively. Therefore, at the beginning of the control period, the robot utilized all the degrees for the visual servoing task (as we can see in the figure, the condition number is 1). Over time, the condition number decreased, and the robot finally decided to eliminate the corresponding degree around 55 [s]. To avoid the instability, the second task was applied after a while, which we can see the lag in the figure. After this, the second task is achieved and the angle converged to the desired $\pi/2$ shown in the figure 3.

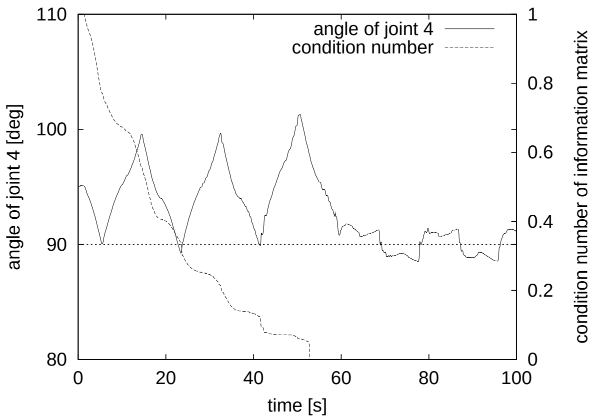

Figure 3: Angle of joint 4 is shown with minimum singular value: after the singular value becomes small, the angle converge to the desired $(\pi/2)$

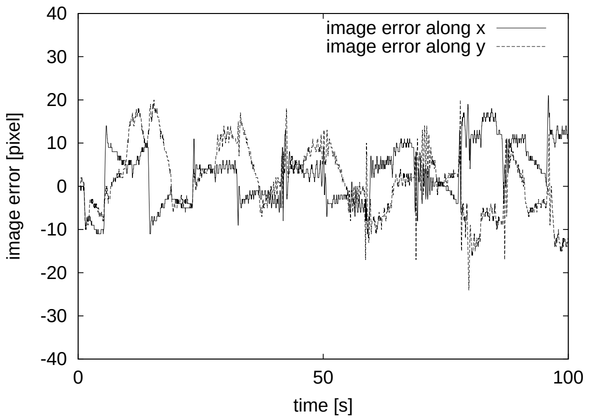

Figure 4: Image error of one image feature along x and y axes of the image plane

In figure 4, the image errors in the image plane are shown. We can see that before and after finding the redundancy, the performances of the visual servoing task are almost identical.

From these results, we see that the robot can find its redundancy with respect to the given task by utilizing the proposed scheme. However, when authors did the experiment, there was a difficulty to find a good forgetting factor ρ and a good threshold ε. To find the redundancy earlier, ρ must be smaller, which made σs rapidly decrease. In this case, ε must also be smaller, otherwise we could not discriminate the redundant degree from non-redundant ones that also decreased according to the small ρ. However, this made the estimated Jacobian matrix $\widehat{\boldsymbol{J}}$ numerically unstable, and robot stopped working.

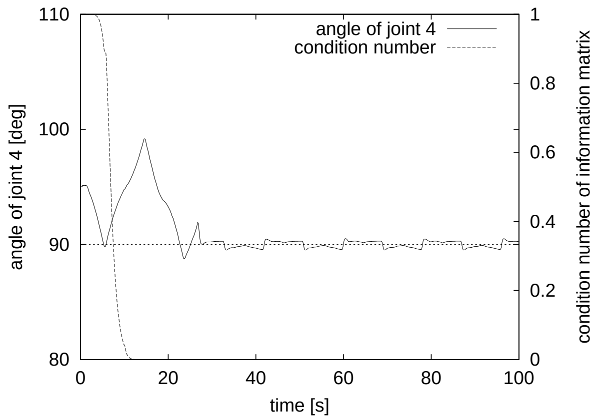

Figure 5: Angle of joint 4 is shown with minimum singular value by the augmented estimator: decreasing speed of the condition number is larger than the previous experiment.

3.3 Experiment 2: Augmented estimator

To avoid this difficulty, an augmented estimator is tested. In the augmented estimator, the estimation of the redundancy is separated from the one of the matrix $\widehat{\boldsymbol{J}}$. To find the redundancy, smaller ρ (in this experiment, 0.95) is used, while rather large one (in this experiment, 1.0) is used for estimating $\widehat{\boldsymbol{J}}$. Then, the estimator can find the redundancy sensitively without losing stability.

In figures 5 and 6, we see the experimental results. By the augmented estimator, the redundancy can be found earlier than the previous method.

4 Conclusion

In this paper, a method to dynamically assign the degrees for the given task is proposed. By experimental results, we have demonstrated that the proposed method can find the redundancy and can utilize it for another task. An augmented estimator is also tested in the experiment that makes the effort of the designer less to determine the appropriate forgetting factor and threshold.

To demonstrate the effectiveness of the proposed method, more experiments are needed by a robot with more external sensors and actuators. For example, the combination between visual servoing and force servoing must be tested with the proposed dynamic DOF assignment.

Our final goal is to build an autonomous adaptive robot that has many degrees of freedom and many

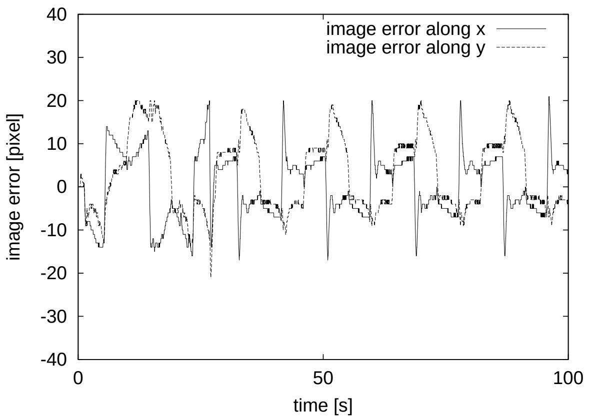

Figure 6: Image error of one image feature along x and y axes of the image plane: the performance of the visual servoing is almost identical with the previous one

sensors in a dynamic environment. The authors have proposed to use such a hybrid structure of adaptive controllers to control multi-degree-of-freedom robots [5–7]. In these papers, each controller can estimate parameters automatically, but cannot find its redundancy with respect to a given task. As a result, the system is less adaptive. If the controller can find redundancy by itself, it can spare the redundant degrees for other controllers, and as a consequence, the over all hybrid structure can deal with more varieties of environments.

References

[1] Y. D. Landau. *Adaptive Control —The Model Reference Approach*. Marcel Dekker, 1979.

[2] J. J. Slotine and W. Li. Adaptive manipulator control: A case study. *IEEE Transaction on Automatic Control*, 33(11):995–1003, 1988.

[3] R. A. Brooks. Intelligence without representation. *Artificial Intelligence*, 47, 1991.

[4] R. C. Arkin. *Behavior-Based Robotics*. The MIT Press, 1998.

[5] K. Hosoda, K. Igarashi, and M. Asada. Adaptive hybrid control for visual servoing and force servoing in an unknown environment. *IEEE Robotics and Automation Magazine*, 5(4):39–43, 1998.

[6] T. Miyashita, K. Hosoda, and M. Asada. Hybrid structure of reflective gait control and visual servoing for walking. In *Proc. of the 1998 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, pages 229–234, 1998.

[7] T. Miyashita, K. Hosoda, and M. Asada. Reflective walk based on lifted leg control and vision-cued swaying control. In *Proc. of 1998 BSMEE International Symposium on Climbing and Walking Robots (CLAWAR'98)*, pages 349–354, 1998.