

AN UNCALIBRATED VISUAL SERVOING USING EVOLUTION STRATEGIES TO ESTIMATE IMAGE JACOBIAN

Kata PRADITWONG, Prabhas CHONGSTITVATANA

Department of Computer Engineering
Chulalongkorn University
Phayathai Road, Bangkok 10330, Thailand
Tel: (662) 218-6983 Fax: (662) 218-6955
E-mail : prabhas@chula.ac.th

Abstract : *This work proposed a method to estimate image Jacobian using Evolution Strategies. The proposed method is used to perform adaptive Jacobian in an uncalibrated visual servoing system. The experiment is carried out under simulation with a three-degree-of-freedom robot arm using two cameras. The result shows that the proposed method when applied to adapt Jacobian performs the visual servoing task with smaller trajectory error than a fixed Jacobian system.*

Keywords: *Visual servoing, image Jacobian, Evolution Strategies.*

1. INTRODUCTION

The control of a robotic hand-eye system requires the knowledge of the arm configuration and the camera position. The kinematic equations describing the system require precise information. Traditionally, the camera calibration is very important. However, in practice where the task requires the mobility of camera, retaining the calibration is very difficult. Numerous works have proposed the uncalibrated system for the control of robotic hand-eye system, which is called *visual servoing*. Some visual features are used as inputs to the control system. The image Jacobian is used to control the robot arm.

Previous works (Conkie & Chongstitvatana, 1990) and (Chancharoen & Sangveraphunsiri, 1999) estimate only initial image Jacobian (J) and use it to derive the control commands with the following relation:

$$\Delta f = J \Delta q \quad (1)$$

Where Δf is the change of image features (the position of the robot's end effector) in an image coordinate and Δq is the change of joints in the robot arm. It is the fact that an image Jacobian is correct only within a small region near the point which it is estimated. The work in (Jagersand, Fuentes & Nelson, 1997) approximated the Jacobian with finite differences, and solved the updated Jacobian by a rank one updating formula in the Broyden formulas. In (Piepmier,

McMurray & Lipkin, 1999a), the control problem is formulated as a nonlinear least-square optimization and later extended in (Piepmier, McMurray & Lipkin, 1999b) to a moving target. The dynamic Jacobian estimation scheme is used to estimate the combined robot and image Jacobians. Experimental results for a two-degree-of-freedom system is demonstrated.

Our work introduces an adaptive image Jacobian system using Evolution Strategies. Evolution Strategies (ES) (Back, Hoffmeister & Schwefel, 1991) is a technique that mimics a natural evolution. The mutation operator creates offspring by adding all components of a parent with normally distributed random numbers. We use a (1+1)-ES system with adaptive σ with $c = 0.82$. ES is used to search among variants of Jacobian to find a good estimate of the Jacobian at the current position. We compare the proposed method with a system using a fixed Jacobian. The result shows that the proposed method achieves higher trajectory accuracy than a fixed Jacobian method.

This paper is organised as follows. The next section presents the proposed method in details. Section 3 describes the experiments. Section 4 discusses the results. Finally we conclude the work in Section 5.

2. ESTIMATING THE IMAGE JACOBIAN

From (1) we can derive the control command for the robot using the image data as

$$\Delta q = J^{-1} \Delta f \quad (2)$$

An initial estimate of the image Jacobian can be done by performing calibration motions as in (Conkie & Chongstitvatana, 1990). However this Jacobian is correct only in a small region near the current position of the end effector. One way to use this information to control a robot arm to reach a target is by moving in small steps.

$$\Delta q = J^{-1}(s \bullet \Delta f) \quad (3)$$

This formula is slightly different from the one used in (Chancharoen & Sangveraphunsiri, 1999). The step size is s . The smaller step achieves higher accuracy, $s < 1$.

Once the robot arm moved away from its initial calibrated position, the Jacobian needed to be adjusted. We used ES to generate a number of variants of the current Jacobian and used the knowledge about the motion that the robot has just been carried out to select the best estimate among these variants. Assume we generate n variants of the current Jacobian. These variants are used to find a set of commands to move the robot joints.

$$\Delta q_n = J_n^{-1}(s \bullet \Delta f) \quad (4)$$

We calculate the expected positions of this set of commands using the previous Jacobian. Let denote the previous Jacobian J_0 .

$$\Delta f_n = J_0 \Delta q_n \quad (5)$$

Using these expected positions, we choose J_n which can best predict the motion along the target line now that the actual motion (using J_0) is already known. The best J_n is the one that the expected position is the nearest complement of the actual position, where the complement position is measured by the angle between the target line and the line of motion. In other words, the best J_n is the one that, if it is used previously, the motion will be closer to the target line. This J_n is used as the Jacobian for the current position.

Next, the Evolution Strategies that is used to generate variants of Jacobian will be explained. Evolution Strategies (Back, Hoffmeister & Schwefel, 1991) developed by Rechenberg and Schwefel, is a search method which mimics the natural evolution. Other popular search method inspired by natural evolution is Genetic Algorithms. This work uses one variant of ES called (1+1)-ES, the population is composed of two individuals, $P = (x, \sigma)$ where x is the object parameter represents a point in search space and σ is the standard deviation. In each generation, the offspring are generated from the parents by adding a random value to the object parameters. The random value has normal distribution with mean equals zero and has the standard deviation σ . This operation is called mutation. The fitness of the offspring is calculated, the better individual will become the parent of the next generation. The standard deviation σ is adjusted according to the 1/5 success rule. This rule states the ratio of the number of offspring that are better than parents to the total number of mutation. If the value is greater than 1/5, σ will be divided by c , otherwise σ is multiply by c , where $c < 1$. In practice, $c = 0.82$ is

used widely. The adjustment of σ is done every k generations.

3. EXPERIMENT

We use MATLAB and Robotics toolbox (Corke, 1996) to model the robot arm. The robot system is composed of one three-degree-of-freedom arm and two cameras. The task is to move the end effector to the visible target. We assume that the end effector and the target are visible in both cameras all the time. We compare the trajectory error between a fixed Jacobian system and our adaptive Jacobian system.

The metrics are 1) the number of moves to reach the target, and 2) the trajectory error, which is measured as the deviation from the straight-line between the initial position of the end effector to the target. Because ES method is non-deterministic, e.g. every run of the algorithm will give slightly different results, we repeat the experiment 1000 times and the data is averaged from all runs. For the fixed Jacobian system, which is deterministic, one run is sufficient.

Six targets are randomly chosen. Two step sizes are tested, 1/4 and 1/10. For ES parameters, we adjust σ every 20 generations and the maximum generation is 100. The initial value of σ is determined from the initial distance between the end effector and the target. The number of variants of Jacobian, n is 100.

4. RESULTS

For the adaptive Jacobian, we report both the average number and its standard deviation. Table 1 and 2 show the result for the step size 1/4. From Table 1, the numbers of moves of two methods are similar but the adaptive Jacobian has smaller trajectory error. Table 3 and 4 show the result for the step size 1/10. Table 3 shows the number of moves, the adaptive Jacobian has a smaller number of moves but its variance is high in some paths. Table 4 shows that the adaptive Jacobian has a much lower trajectory error. The reason why the adaptive Jacobian did not achieve a smaller number of moves is that the ES tries to minimise the trajectory error, not the number of move. Figure 1 shows typical trajectories of two methods in reaching a target.

Overall, the adaptive image Jacobian has a trajectory error smaller than the fixed image Jacobian. The difference of the number of moves is small between two systems. Using a smaller step size, 1/10, the trajectory error is smaller. The reason for the improvement is because ES has more time to evolve under the smaller step size.

5. CONCLUSION

We have demonstrated that the proposed method to estimate the image Jacobian using Evolution Strategies

performed better than a fixed Jacobian system for a visual servoing task. The experiment clearly demonstrates that an adaptive Jacobian system using evolutionary approach can work very well. The main advantage of ES system is that it is possible to cope with high-dimensional problems. We are investigating the manipulation problem with higher dimensions and we are validating this method with a real robot.

6. REFERENCES

- Back, T. Hoffmeister, F, Schwefel, H. A survey of Evolution Strategies. In Proceedings of the Fourth International Conference on Genetic Algorithms, Morgan Kaufmann, 1991.
- Chanchaen, R., and Sangveraphunsiri V. An Image Based Visual Servo Control For Industrial Robots. In Proceedings of The First Asian Symposium on Industrial Automation and Robotics, pages 107-110, Bangkok, Thailand, 1999.
- Conkie A., Chongstivatana P. An Uncalibrated Stereo Visual Servo System. In Proceedings of the British Machine Vision Conference, pages 277-280, Oxford, 1990.
- Corke P. I. A robotics toolbox for MATLAB, IEEE Robotics and Automation, pages 24-32, March 1996.
- Jagersand M., Fuentes O., and Nelson R. Experimental Evaluation of Uncalibrated Visual Servoing for Precision Manipulation. In Proceedings of International Conference on Robotics and Automation, pages 2874-2880, New Mexico, April 1997.
- Piepmeyer J. A., McMurray G. V., and Lipkin H. A Dynamic Quasi-Newton Method for Uncalibrated Visual Servoing. In Proceedings of International Conference on Robotics and Automation, pages 1595-1600, Michigan, May 1999a.
- Piepmeyer J. A., McMurray G. V., and Lipkin H. A Dynamic Jacobian Estimation Method for Uncalibrated Visual Servoing. In Proceedings of International Conference on Advanced Intelligent Mechatronics, pages 944-949, Atlanta, September 1999b.
- Winter G., Periaux J., Galan M., Cuesta P., Genetic Algorithms in Engineering and Computer Science, John Wiley & Sons, 1995.

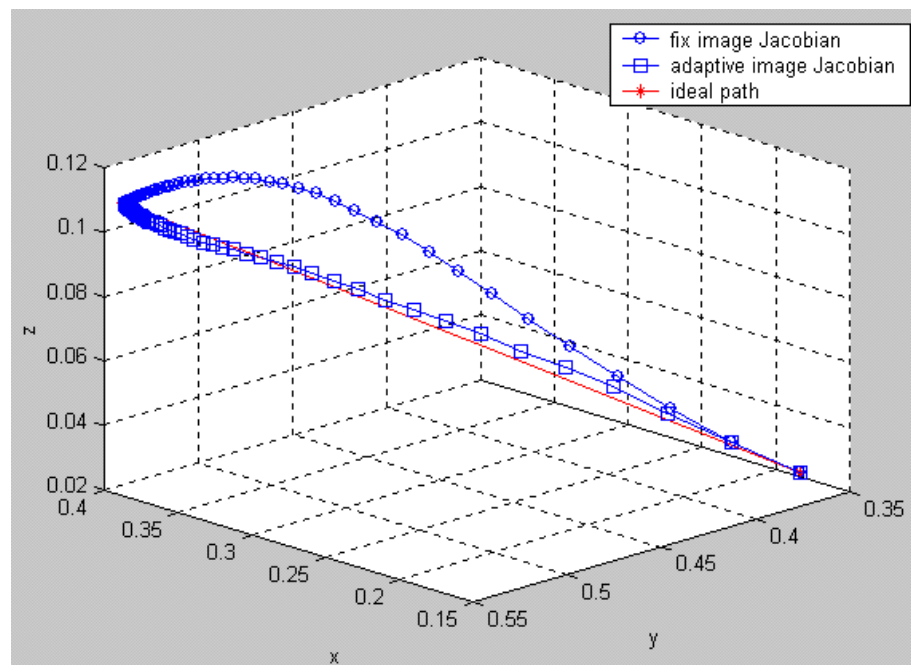


Fig. 1. Comparing the trajectory between Fixed and Adaptive Jacobian method.

Table 1 The number of moves with the step size 1/4

Path No.	1	2	3	4	5	6
Fixed Jacobian	22	17	21	21	33	24
Adaptive Jacobian	19	17	28	21	32	23
STD	1.42	1.55	6.21	3.90	3.46	1.58

Table 2 The trajectory error with the step size 1/4

Path No.	1	2	3	4	5	6
Fixed Jacobian	0.49	0.29	0.64	0.60	1.42	2.01
Adaptive Jacobian	0.31	0.15	0.68	0.46	1.19	1.83
STD	0.05	0.03	0.09	0.09	0.17	0.18

Table 3 The number of moves with the step size 1/10

Path No.	1	2	3	4	5	6
Fixed Jacobian	57	46	56	57	86	65
Adaptive Jacobian	46	46	61	54	77	56
STD	1.74	1.41	8.30	2.12	10.11	3.68

Table 4 The trajectory error with the step size 1/10

Path No.	1	2	3	4	5	6
Fixed Jacobian	0.47	0.27	0.59	0.56	1.36	1.85
Adaptive Jacobian	0.09	0.07	0.55	0.08	0.73	0.79
STD	0.04	0.02	0.22	0.04	0.16	0.33