An LPV Approach to Synthesizing Robust Active Vision Systems

Mario Sznaier Brian Murphy Octavia Camps
Department of Electrical Engineering
The Pennsylvania State University
University Park, PA 16802
email: {msznaier,brian}@gandalf.ee.psu.edu, camps@whale.ee.psu.edu

Abstract

Recent hardware developments have rendered controlled active vision a viable option for a broad range of practical problems. However, realizing this potential requires having a framework for synthesizing robust active vision systems, capable of moving beyond carefully controlled environments. Recent work has shown that this can be achieved by combining robust computer vision and control techniques. However, in some cases robustness is achieved at the expense of performance. In this paper we show that this performance loss can be avoided by recasting the problem into a Linear Parameter Varying (LPV) form and using recently developed robust identification and control tools for this class of problems. These results are experimentally validated using a Bisight robotic head.

1 Introduction and Motivation

Recent hardware advances have rendered *visual feedback* a viable option for a very diverse spectrum of applications ranging from MEMS manufacture[7] to assisting individuals with disabilities [23], and Intelligent Vehicle Highway Systems [18]. Clearly these applications would not be possible without the use of feedback control to compensate for uncertainty and errors.

Active vision systems appeared as far back as late 1970's [10] and have been the subject of much research since. An excellent survey of the earlier work (up to 1996) can be found in [12].

Earlier active vision systems dealt with stability issues by detuning the controller, at the expense of performance, until stability was accomplished [12]. Latter approaches combined PID controllers with some prediction to explicitly address time delays. However, these predictors can tolerate only small amounts of uncertainty [15]. Moreover, the combination PID controller/predictor had to be tuned empirically, a process that entailed considerable experimentation [6].

Set–point tracking can be improved using a two–degrees of freedom (2–DOF) controller [6]. However, this approach can improve neither robustness nor disturbance rejection. Optimal controllers have the potential to improve performance [14, 9], but can lead to fragile systems [14]. Empirical results [13, 17] show that adaptive controllers can accommodate calibration errors. However, this approach does not allow for achieving an a–priori established robustness level or to balance robustness versus performance.

Arguably, at this point fragility is one of the critical factors limiting widespread use of active vision techniques. Indeed, while commercially available products offer basic object–tracking, they have very limited robustness capabilities and lack flexibility [11].

Very recent work has recognized the fact that robustness issues are central to the success of active vision systems. Robustness to calibration errors and estimation noise has been addressed in [8, 22] and [16] respectively. Robustness against unmodelled dynamics and parametric uncertainty has been addressed in [20]. However, in all these cases robustness is potentially obtained at the expense of performance.

In this paper we illustrate with a simple example the control–related issues involved in active vision and we show how some very recently developed Linear Parameter Varying (LPV) control techniques can be brought to bear on the problem. These results are experimentally validated using a stereo–head. Finally, the paper ends by pointing–out new research directions and possible extensions of currently available techniques.

2 Preliminaries

2.1 Hardware description

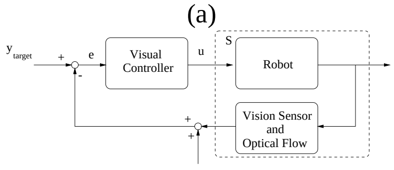
The hardware setup used in this paper, shown in Figure 1 (a), consists of a Unisight pan/tilt platform with a BiSight stereo head with Hitachi KP-M1 cameras and Fujinon H10X11EMPX-31 motorized lenses. The input commands to the head and the lenses were given using a 10 channel PMAC $\delta - \tau$ controller. The image processing was performed using a Datacube MaxSPARC S250 hosted by a Sun Ultra Sparc workstation.

In the next section we use this setup as a vehicle to illustrate some problems with currently available techniques and to motivate the proposed approach. For the sake of briefness, in the sequel we concentrate only on controller design for the pan axis. Control design for the second axis (tilt motion) follows exactly along the same lines.

2.2 Illustrative example

The control–related issues involved in active vision can be illustrated by considering the problem of smooth tracking of a non–cooperative target, illustrated in the block diagram shown in Figure 1 (b). Here the goal is to internally stabilize the plant and to track the reference signal y_{ref}, using as measurements images possibly corrupted by noise.

(a)



(b)

Figure 1: (a) The experimental setup, (b) Block diagram of a visual tracking system.

Control oriented identification of the plant yields the following model for the nominal transfer function from the command input to the tracking error (in pixels, see [20] for details):

$$G_{nom}(z) = \frac{0.016z^5 + 0.088z^4 + 0.193z^3 + 0.077z^2 + 0.045z + 0.077}{z^5 + 0.385z^4 + 0.837z^3 + 0.38z^2 + 0.29z + 0.076} \times \frac{1}{z^2} \quad (1)$$

where the factor $\frac{1}{z^2}$ models the image processing delay.

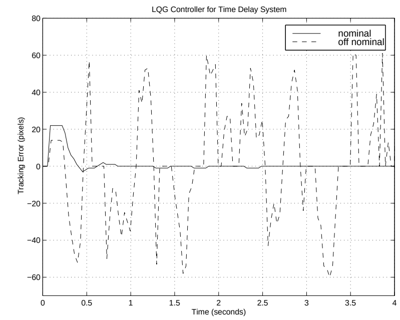
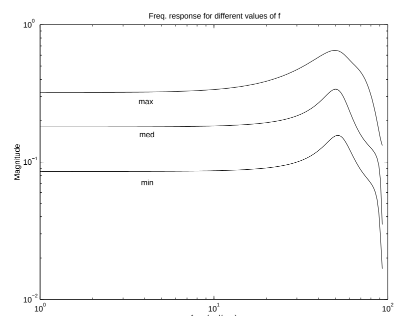
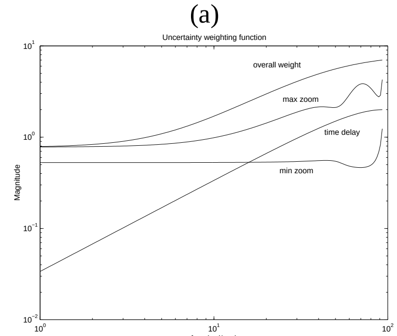


Figure 2: Tracking error of an optimal LQG controller (experimental).

Once the model (1) has been obtained, a controller can be synthesized using standard techniques. Figure 2 shows experimental results obtained using an LQG controller tuned to achieve a compromise between settling time and overshoot. Note that while the controller achieves acceptable performance for the nominal plant, the closed–loop system becomes unstable for off–nominal conditions[1].



(a)



(b)

Figure 3: (a) Open loop frequency responses for different f's (b) Selection of the uncertainty weight.

[1] Similar results were also obtained with a PID controller. These results are omitted for space reasons.

This phenomenon can be easily explained by looking at the transfer functions corresponding to different values of the focal length f, shown in Figure 3 (a). As shown there, changes in f effectively amount to a change in a gain multiplying the control action, leading to instability when the gain margin of the system is exceeded.

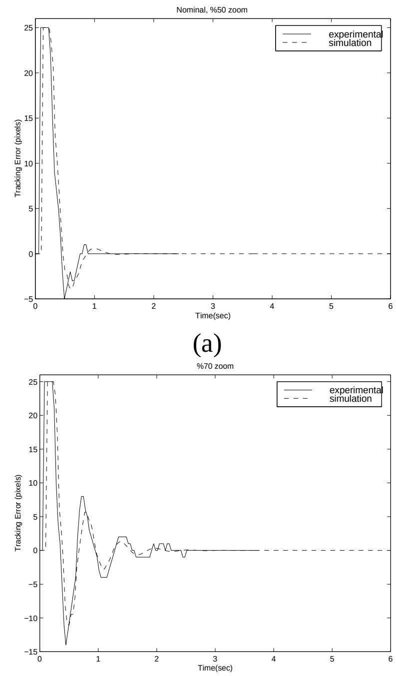
This difficulty can be solved by modelling the system as a nominal plant subject to multiplicative dynamic uncertainty (intended to cover, in addition to variations in f, unmodelled dynamics and uncertainty in the time–delay), and using robust control tools to synthesize a controller guaranteeing robust performance. Figure 3 (b) shows the uncertainties corresponding to the minimum and maximum values of the zoom f, and up to one–sampling period in the time–delay (the total time delay fluctuates between two and three sampling periods depending on the amount of time required to locate the target in the image). From these plots it follows that a suitable uncertainty weight is given by:

$$W_u(z) = \frac{4.7z - 3.9}{z - 0.08} \tag{2}$$

Finally, in order to guarantee perfect tracking of step displacements, the plant was augmented with an integrator at the control input. Using μ–synthesis with first order scales and performance weigth $W_p(z) = \frac{2.3z+0.56}{z-0.72}$[2] leads to a 10^{th} order controller. The step responses of the closed loop system obtained with this controller (simulation and experimental) for two different values of f are shown in Figure 4. As shown there, in the nominal case performance is similar (in terms of overshoot and settling time) to that achieved with the LQG controller. On the other hand, changes in f result in somewhat degraded performance, but the system still remains stable.

This example illustrates the ability of the combination of robust identification and robust control techniques to address the fragility exhibited by active vision systems designed using classical techniques. However, in some cases this robustness is achieved at the expense of performance. For instance, experimental results obtained in our lab show that this approach works well when f is allowed to change between 30% to 70% of its range, but it entails substantial performance loss otherwise. Simply put, one is asking a *single* controller to accommodate a large range of plant dynamics and this can be accomplished only by using a small gain, leading to relatively slow systems. As we show in the sequel, performance can be regained by casting the active vision problem into an LPV form.

[2] This function has a low pass characteristic, penalizing large tracking errors and leading to a closed loop function with a bandwidth on the order of $10Hz$ (equivalently, settling times on the order of 0.5 sec.).



(a)

(b)

Figure 4: Tracking error for a robust controller: (a) 50% zoom (nominal), (b) 70% zoom

3 Improving performance using a Linear Parameter Varying Approach

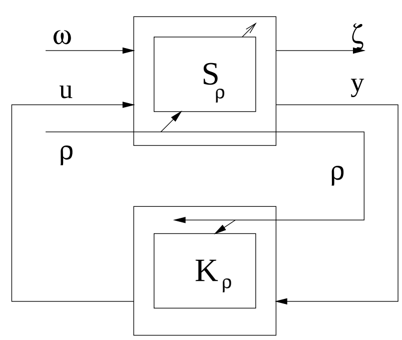


Figure 5: General LPV System

Most active vision setups allow for measuring parameters (such as f and the distance Z_s to the target in real time [3], albeit corrupted by noise). Thus, the system can be recast in the form shown in Figure 5 where the plant depends on time–varying parameters that are unknown a–priori, but can be measured on–

line. Problems involving these types of systems (linear parameter varying (LPV)) have been the object of recent attention in the control community. While a comprehensive theory is still being developed, some tools are already available that allow for optimizing performance while guaranteeing stability [24]. Since in this approach the controller depends explicitly on the present values of these parameters, it has the potential to outperform a fixed linear controller designed to accommodate the entire parameter range. Successful application of this approach to active vision systems requires development of tools for:

1.- Robust identification of LPV models

2.- Real time self-calibration and depth estimation

3.- Synthesis of robust LPV controllers that accommodate the special features of active vision problems.

In this paper we will consider only items (1) and (3) above, assuming that measurements of the relevant parameters are available. Some open issues concerning these measurements and their impact in the controller design are discussed in section 5.

3.1 Control Oriented Identification of LPV systems

The first step in applying LPV tools to the active vision problem is to identify a model suitable to be used by the available control synthesis methods. A difficulty here is that while control oriented identification of LTI systems is by now relatively mature [15], comparable identification tools for LPV systems are just starting to appear. In this paper we will use the robust LPV identification framework recently proposed in [21], that starting from experimental data and some mild *a priori* assumptions on the plant, generates a nominal model as well as bounds on the worst case identification error suitable to be used by LPV robust control synthesis methods.

The experimental information considered consisted of $Nt = 25$ samples of the time response of the real system y_k to a known input u_k while the time varying parameter ρ_k (in this case the focal length) was allowed to vary between -0.5977 and 0.2076 during the experiment. By repeatedly measuring the location of the centroid of the target in the absence of input, the experimental noise measurement was determined to be bounded by $\epsilon_t = 4/110$pixels/count [3]. Based on this data we obtained the following LPV model:

[3] This experimental error is mainly due to fluctuating conditions such as ambient light.

$$
\begin{aligned}
x_{k+1} &= \left[A_P + \rho_k B_{P2}(I - \rho_k D_{P22})^{-1} C_{P2}\right] x_k \\
&+ \left[B_{P1} + \rho_k B_{P2}(I - \rho_k D_{P22})^{-1} D_{P21}\right] u_k \\
y_k &= p\left\{\left[C_{P1} + \rho_k D_{P12}(I - \rho_k D_{P22})^{-1} C_{P2}\right] x_k\right. \\
&+ \left.\left[D_{P11} + \rho_k D_{P12}(I - \rho_k D_{P22})^{-1} D_{P21}\right] u_k\right\}
\end{aligned} \tag{3}
$$

where:

$$
\begin{aligned}
A_P &= \begin{bmatrix}
0.3787 & 0.7251 & 0.1290 & -0.0038 & 0.1462 & -0.0208 & 0.0093 \\
-0.7251 & -0.1105 & 0.3192 & -0.0430 & 0.2293 & -0.0156 & 0.0110 \\
0.1290 & -0.3192 & -0.5908 & 0.4262 & 0.3062 & -0.0774 & 0.0244 \\
0.0038 & -0.0430 & -0.4262 & -0.8815 & 0.1401 & -0.0178 & 0.0075 \\
-0.1462 & 0.2293 & -0.3062 & 0.1401 & 0.4621 & 0.3085 & -0.0582 \\
-0.0208 & 0.0156 & -0.0774 & 0.0178 & -0.3085 & 0.7302 & 0.1708 \\
-0.0093 & 0.0110 & -0.0244 & 0.0075 & -0.0582 & -0.1708 & 0.8409
\end{bmatrix} \\
B_{P1} &= \begin{bmatrix} 0.4848 \\ 0.3815 \\ 0.1992 \\ 0.0491 \\ -0.0941 \\ 0.0121 \\ -0.0009 \end{bmatrix}, \; B_{P2} = B_{P1}; \; C_{P1} = \begin{bmatrix} 0.1212 \\ -0.0954 \\ 0.0498 \\ -0.0123 \\ 0.0235 \\ 0.0030 \\ 0.0002 \end{bmatrix}^T \\
C_{P2} &= 0_{1\times 6}, \; D_{P11} = -0.0059, \; D_{P12} = D_{P11}, \; D_{P21} = 1, \\
D_{P22} &= 0, \; p = 1.0799.
\end{aligned} \tag{4}
$$

Figure 6 compares the output of the identified model against the experimental data. As shown there, the identified model explains the observed data within the experimental error.

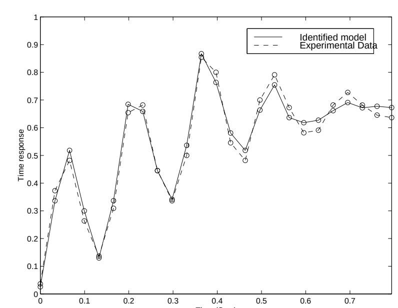
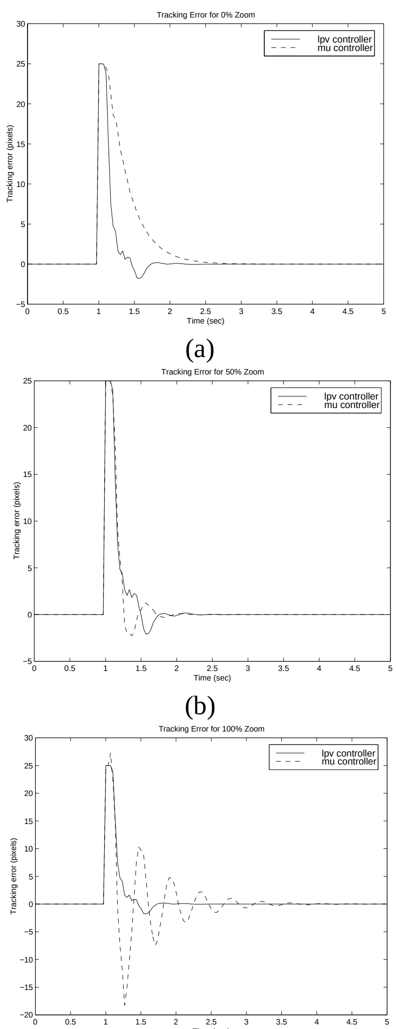


Figure 6: Output of the identified LPV model and experimental data

4 Controller Design

A difficulty in synthesizing LPV controllers for active vision systems is that currently available techniques assume that the controller has instantaneous access to exact values of the parameters. On the other hand, in active vision problems these parameters must be estimated from images, leading to delays and some level of uncertainty. Nevertheless, these factors can be taken into account, albeit in a somewhat conservative fashion, by incorporating them into the model uncertainty and designing a robust LPV controller. In the sequel we pursue this approach, using the technique proposed in [4] to design an LFT scheduled $\mathcal{H}_\infty$ controller. It can be shown that in this context, the problem reduces to an LMI feasibility problem that can be efficiently solved.

Figure 7 compares the performance of the LPV controller[4] against that achieved by the μ–synthesis based one. As expected, while performance is comparable for the nominal case, the LPV controller yields substantially better performance for off–nominal conditions.



(a) (b) (c)

Figure 7: LPV versus μ controllers:(a) 0% zoom (b) 50% zoom (c) 100% zoom

[4] A state space realization of the controller, omitted for space reasons, can be obtained contacting the authors

5 Conclusions and Directions for Further Research

Recent hardware developments have opened up the possibility of applying active vision techniques to a broad range of real–world problems. However, as noted in recent conferences [1, 2] involving both control and computer vision researchers, while there seems to be a consensus in these communities about the implicit power of visual control, actually realizing this potential requires controllers capable of accommodating, in addition to uncertainty, the substantial time delays and time–varying parameters typical of visual servoing problems. As shown in this paper, the combination of very recently developed LPV robust identification and control tools has the potential to address these issues, leading to controllers capable of achieving good performance for a wide range of operating conditions.

Some issues still open that were not addressed in this paper include:

1. **Multiple performance objectives:** In this paper all performance specifications were given in terms of a single norm (ℓ^2–induced) also used to assess stability. Clearly, a single norm is usually not enough to capture different, and often conflicting, design specifications. For instance the ℓ^2–induced norm, while adequate to address robustness considerations, is not well suited for directly optimizing the size of the region in the image that can be reached by the target (fovea). The larger this region is, the more computationally expensive it becomes to find the target in each frame, resulting in larger time–delays, which in turn limits tracking of fast–moving targets and can compromise stability. Addressing these issues requires expanding the available LPV formalism to handle multiple objectives. A possible way of achieving this is by extending the LMI–based multiobjective techniques proposed in [5] to the LPV case.
2. **Noise and time–delays** in the parameter estimates. As mentioned in section 4, in this paper we have assumed that exact current values of the parameters are available to the controller. However, these values are usually corrupted by noise and delayed. Addressing these issues will require expanding LPV techniques to handle this case.
3. **Model (In)Validation of LPV Systems:** In order to obtain less conservative results, methods should be developed to obtain tight uncertainty characterizations. This can be achieved by developing LPV counterparts of model validation methods currently available for LTI systems[19].

Acknowledgements

The authors are indebted to Ms. C. Mazzaro and Mr. Tamer Inanc for their help in identifying the models of the plant.

References

[1] In *Block Island Workshop on Vision and Control*. Block Island, Rhode Island, June 1997.

[2] In *IEEE Conf. Decision and Control*. 1998. Invited Session: Active Vision: A New Challenge for Control Theory, O. Camps and M. Sznaier Organizers.

[3] L. Agapito, R. I. Hartley, and E. Hayman. Linear self-calibration of a rotating and zooming camera. In *Proc. IEEE Computer Vision and Pattern Recognition*, pages 15–21, 1999.

[4] P. Apkarian and P. Gahinet. A convex characterization of gain–scheduled $\mathcal{H}_\infty$ controllers. *IEEE Trans. Autom. Contr.*, 40(5):853–864, 1995.

[5] J. Bu and M. Sznaier. A linear matrix inequality approach to synthesizing low order mixed $\ell^1/\mathcal{H}_p$ controllers. *Automatica*, 36(7):957–963, 2000.

[6] P. I. Corke and M. C. Good. Dynamic effects in visual closed–loop systems. *IEEE Transactions on Robotics and Automation*, 12(5):671–683, 1996.

[7] J. Feddema. Microassembly of micro–electromechanical systems (MEMS) using visual servoing. In *Block Island Workshop on Vision and Control*, 1997.

[8] G. Hager. A modular system for robust positioning using feedabck from stereo vision. *IEEE Transactions on Robotics and Automation*, 13(4):582–595, 1997.

[9] K. Hashimoto and H. Kimura. LQ optimal and nonlinear approaches to visual servoing. In K. Hashimoto, editor, *Visual Servoing*, volume 7, pages 165–198. World Scientific Series in Robotics and Automated Systems, World Scientific, Singapore, 1993.

[10] J. Hill and W. T. Park. Real time control of a robot with a mobile camera. In *9^{th} ISIR*, pages 233–246, Washington D.C., March 1979.

[11] E. H. Huber and D. Kortenkamp. Using stereo vision to pursue moving agents with a mobile robot. In *1995 IEEE Conf. Robotics and Automation*, 1995.

[12] S. Hutchinson, G. D. Hager, and P. I. Corke. A tutorial on visual servo control. *IEEE Transactions on Robotics and Automation*, 12(5):651–670, 1996.

[13] N. P. Papanikolopoulos. Integrating computer vision and control for vision assisted robotics tasks. In *1995 American Control Conference*, pages 904–908, Seattle, WA, June 1995.

[14] N. P. Papanikolopoulos, P. K. Khosla, and T. Kanade. Visual tracking of a moving target by a camera mounted on a robot: A combination of control and vision. *IEEE Transactions on Robotics and Automation*, 9(1):14–35, 1993.

[15] R. S. Sanchez Pena and M. Sznaier. *Robust Systems Theory and Applications*. John Wiley, New Jersey, 1998.

[16] O. Shakernia, Y. Ma, T. J. Koo, J. Hespanha, and S. S. Sastry. Vision guided landing of an unmanned air vehicle. In *Proc. 1999 IEEE CDC*, pages 4143–4148, December 1999.

[17] C. E. Smith, S. A. Brandt, and N. P. Papanikolopoulos. Eye in hand robotic tasks in uncalibrated environments. *IEEE Transactions on Robotics and Automation*, 13(6):903–914, 1997.

[18] C. E. Smith, C. A. Richards, S. A. Brandt, and N. P. Papanikolopoulos. Visual tracking for intelligent vehicle–highway systems. *IEEE Trans. Vehicular Tech.*, 45(4):744–759, 1996.

[19] R. S. Smith and J. C. Doyle. Model validation: A connection between robust control and identification. *IEEE Trans. Autom. Contr.*, 37(7):942–952, 1992.

[20] M. Sznaier, T. Inanc, and O. Camps. Robust controller design for active vision systems. In *2000 American Control Conference*, pages 2013–2017, 2000.

[21] M. Sznaier, C. Mazzaro, and T. Inanc. An LMI approach to control oriented identification of LPV systems. In *2000 American Control Conference*, pages 3682–3686, 2000.

[22] C. Taylor, J. Ostrowski, and S. H. Jung. Robust visual servoing based on relative orientation. In *1999 CVPR*, July 1999.

[23] J. K. Tsotsos, G. Verghese, S. Dickinson, M. Jenkin, A. Jepson, E. Milios, F. Nuflo, S. Stevenson, M. Black, D. Metaxas, S. Culhane, Y. Ye, and R. Mannn. PLAYBOT: A visually-guided robot for physically disabled children. *Image and Vision Computing*, 16(4):275–292, April 1998.

[24] F. Wu, X. H. Yang, A. Packard, and G. Becker. Induced $\mathcal{L}_2$ norm control for LPV systems with bounded parameter variation rates. *Int. J. Robust and Nonlinear Contr.*, 6(9/10):983–998, 1996.