A Vision-Based Dual Anticipatory/Reactive Control Architecture for Indoor Navigation of an Unmanned Aerial Vehicle Using Visual Topological Maps

Darío Maravall, Javier de Lope, and Juan Pablo Fuentes Brea

Department of Artificial Intelligence, Faculty of Computer Science, Universidad Politécnica de Madrid, Madrid, Spain - Centro de Automática y Robótica (UPM-CSIC) Universidad Politécnica de Madrid, Madrid, Spain
dmaravall@fi.upm.es, javier.delope@upm.es,
juanpablo.fuentes.brea@alumnos.upm.es

Abstract. Indoor navigation of an unmanned aerial vehicle is the topic of this article. A dual feedforward/feedback architecture has been used as the UAV´s controller and the K-NN classifier using the gray level image histogram as discriminant variables has been applied for landmarks recognition. After a brief description of the aerial vehicle we identify the two main components of its autonomous navigation, namely, the landmark recognition and the controller. Afterwards, the paper describes the experimental setup and discusses the experimental results centered mainly on the basic UAV´s behavior of landmark approximation which in topological navigation is known as the beaconing or homing problem.

Keywords: Unmanned Aerial Vehicles, Vision-based dual anticipatory reactive controllers, Nearest Neighbors Methods.

1 Introduction

For the autonomous navigation of the UAV we have used a visual topological map in which the landmarks or relevant places are modeled as the vertices of a labeled graph and the edges correspond to specific UAV´s maneuvers.

As the landmarks are visual references, a fundamental problem in visual topological navigation is landmark recognition, so that we devote a complete section of the paper to this topic (see paragraph 2 below "Automatic Recognition of Visual Landmarks").

For the UAV´s controller we have applied a vision-based dual feedforward / feedback control architecture. In the sequel we describe both components of the UAV´s navigation: first, landmark recognition and afterwards, the dual controller.

The paper ends with the experimental work in our laboratory and the final conclusions.

J.M. Ferrández Vicente et al. (Eds.): IWINAC 2013, Part II, LNCS 7931, pp. 66–72, 2013.

1.1 Unmanned Aerial Vehicles (UAV)

An UAV can be regarded as a autonomous robot and it has the capacity to fly within an environment, in this paper through indoor environment. We are using the quadrotor Parrot AR.Drone 2.0 [8] as robotics research platform, available to the general public.

All commands and images are exchanged with controller via a WiFi ad-hoc connection. The AR.Drone has a vision sensor implemented as a HD camera, and has four motors to fly through the environment.

Fig. 1. Parrot AR.Drone 2.0

This UAV support four types of movement along its axes $(roll, pitch, gaz, yaw)$ allowing you to move on the three coordinates of the space 3D (x, y, z): sideways, forward/back, vertical speed and rotation about its vertical axis.

The AR.Drone can be used for visual autonomous navigation in environments using machine learning approaches, and it's used in many applications as surveillance tasks, rescue tasks, and can perform human-machine interactions.

2 Automatic Recognition of Visual Landmarks

The UAV´s navigation system utilizes the onboard camera to capture the environment images. These images are classified and used by the controller in order to generate the control command s in real time. More specifically, as the navigation system is based on a topological map it is vital to have an efficient classification of the landmarks images to guarantee a correct guidance of the UAV.

For landmark recognition we have used the gray levels standard histogram as the discriminant variables and the k-NN algorithm as the classifier. As it is well-known, the k-NN algorithm is an efficient memory-based classifier based on a stored data base of labeled exemplars and any new case to be recognized is assigned the most frequent class among the k nearest neighbors in the training data base.

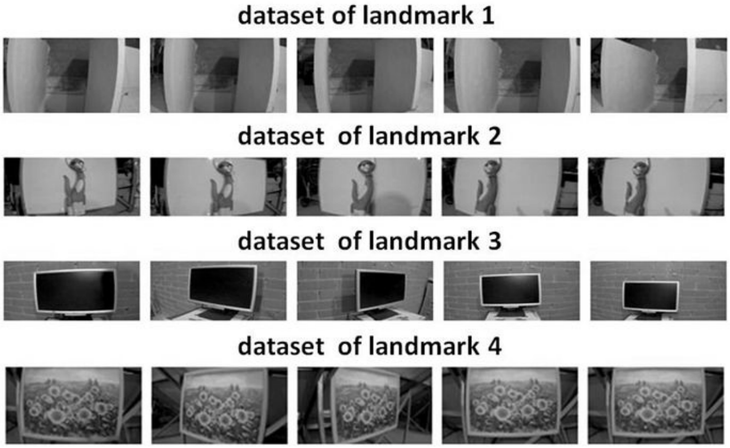

Fig. 2. Dataset of several visual landmarks

To evaluate the performance in landmark recognition we have generated a training data set formed by four different landmarks [7] displayed in Fig. 2. Notice that in the data set are actually stored the gray level histograms of the corresponding landmark images.

In our experiments we have considered four landmarks: a picture, a TV set, a sculpture and a door. For the classifier evaluation we have applied the leaving-one-out crossvalidation technique.

During the experimental validation of the k-NN algorithm we have tried several values of the design parameter: k = 1, 2 and 3. For all cases we have obtained excellent results with a classification error close to 0%. Fig. 3 displays a typical confusion matrix.

	predicted class 1	predicted class 2	predicted class 3	predicted class 4
actual class = 1	**10**	0	0	0
actual class = 2	0	**10**	0	0
actual class = 3	0	0	**10**	0
actual class = 4	0	0	0	**10**

Fig. 3. Confusion matrix

Apart from the efficiency of the k-NN algorithm itself we believe that the excellent recognition results obtained are mainly due to the discriminant variables provided by the graylevel histogram of the landmarks images.

3 The Feedforward/Feedback Controller

Fig. 4 displays the block-diagram of the dual feedforward / feedback controller [4][6]. Notice that both the feedforward or anticipatory controller and the feedback or reactive controller [2][3] receive as input the same image error, which is the difference between the target or desired image (i.e. the image corresponding to the current identified landmark) and the current image captured by the UAV´s on board camera.

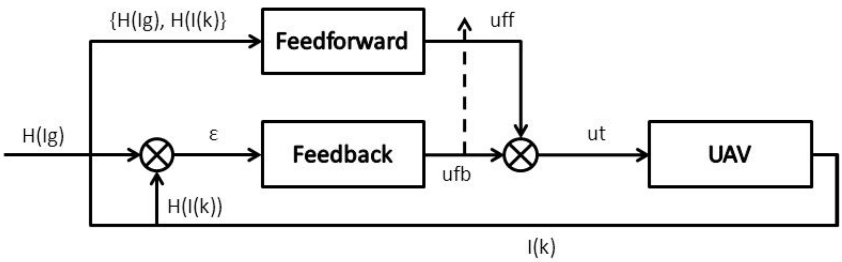

Fig. 4. The feedforward/feedback controller: Notice that the error signal of both controllers is obtained as the difference between the histogram of the recognized landmark or histogram of the goal image $H[Ig]$ and the histogram of the current image $H[I(k)]$

More specifically, this vision-based error signal is obtained as the histogram of the identified landmark or histogram of the goal image $H[Ig]$ minus the histogram of the current UAV´s captured image $H[I(k)]$ during the k iteration of the controller. The feedback controller is implemented as a conventional PD control [5] and the feedforward controller is based on a inverse model [1] using a conventional neural network based algorithm.

4 Experimental Work: UAV´s Navigation through Doors

To test experimentally the proposed vision-based dual controller we have chosen the basic UAV´s navigation skill of "door approaching and crossing". The basic idea to test this UAV´s navigation skill is to get the UAV to fly towards a door as a target landmark in its visual topological map. Once the UAV is approaching its target landmark and after its correct recognition it can activate its dual vision-based controller in order to safely transverse the door by monitoring and controlling the visual error.

Fig. 5 display a sequence of the images captured by the onboard UAV´s camera while performing a door navigation maneuver. We have also displayed in Fig. 6 the visual error signal that converges to zero as expected during this door navigation maneuver.

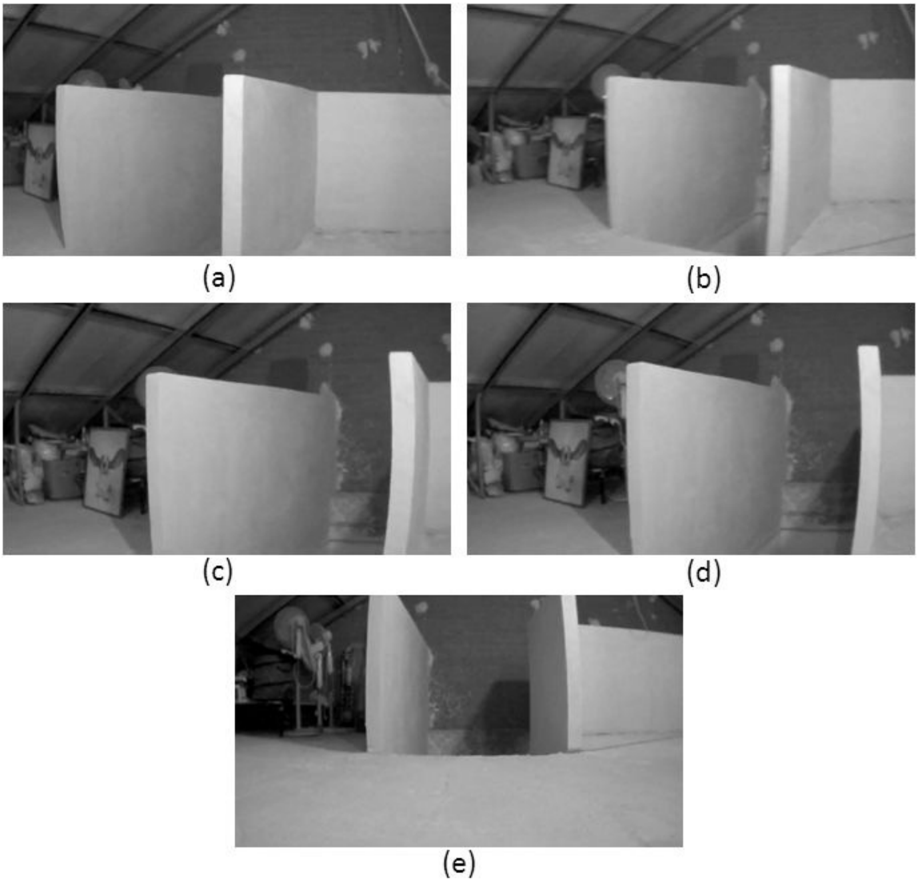

Fig. 5. Notice that the sequence (a)-(e) includes the successive images captured by the UAV while performing the maneuver: (a) is the initial state and (e) is the goal image

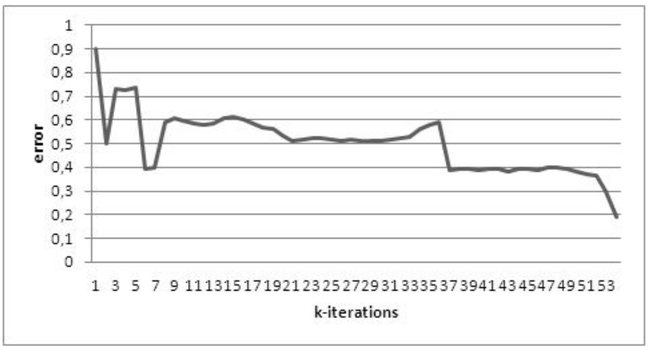

Fig. 6. The visual error signal during the door-landmark approximation and crossing maneuver

Notice also the control curves in Fig. 7 giving an idea of the UAV´s control efforts applied during this maneuver. In both cases, k denotes the number of iterations of the controller during the maneuver (sequence (a)-(e)): (a) and (b) have been caught between k=1 and k=9, (c) and (d) between k=10 and k=39, and finally (e) corresponds from k=40 to the end of the maneuver. At each iteration, the controller sends a control signal to the UAV; the time between two consecutive control signals is 30 ms.

During this approaching experiment, the UAV has used the pitch actuator (forward / back) and yaw actuator (rotation on its axis z), which were obtained by the controller based on the error signals received by the classifier k-NN.

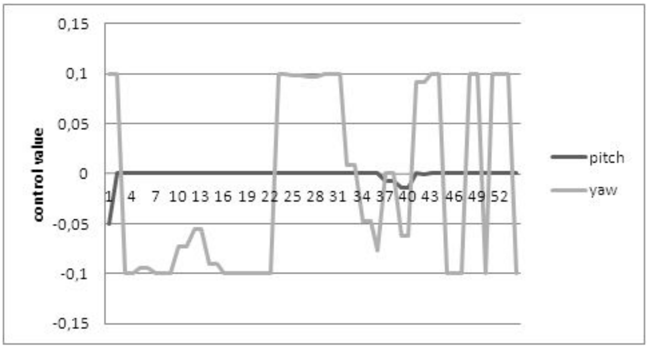

Fig. 7. The control signals during the door approximation and crossing maneuver

From the experimental results obtained in our laboratory and shown in Figures 6 and 7 we can conclude that the UAV is able to successfully perform in real time the fundamental skill of landmark door approximation and crossing by mean of the propossed vision-based dual feedforward/feedback controller.

5 Conclusions and Future Work

This paper has presented a vision-based dual anticipatory/reactive controller for indoor navigation of an UAV that uses a visual topological map to autonomously navigate in the environment. We have also described the basic problem of visual landmark recognition for which we have implemented a k-NN classifier using the standard graylevel histogram values as discriminant variables, giving excellent recognition accuracy. The proposed navigation system has been experimentally tested on the basic skill of door-landmark approximation and crossing maneuver. Future work is planned towards the UAV´s autonomous navigation in a whole building by means of a visual topological map of a complete building.

References

1. Kawato, M.: Feedback-Error-Learning Neural Network for Supervised Motor Learning. In: Advanced Neural Computers (1990)
2. Wolpert, D.M., Kawato, M.: Multiple paired forward and inverse models for motor control. Neural Network 11, 1317–1329 (1998)
3. Kawato, M.: Internal models for motor control and trajectory planning. Neurobiology 9, 718–727 (1999)
4. Imamizu, H., Kawato, M., et al.: Human cerebellar activity reflecting an acquired internal model of a new tool. Nature 403, 192–195 (2000)
5. Maravall, D., de Lope, J.: Multi-objective dynamic optimization with genetic algorithms for automatic parking. Soft Computing 11(3), 249–257 (2007)
6. Barlow, J.S.: The Cerebellum and Adaptive Control. Cambridge University Press (2002)
7. Maravall, D., de Lope, J., Fuentes, J.P.: Fusion of probabilistic knowledge-based classification rules and learning automata for automatic recognition of digital images. Pattern Recognition Letters (in press, 2013)
8. Piskorski, S., Brulez, N., D'Haeyer, F.: AR.Drone Developer Guide SDK 2.0, Parrot (2012)