

EUROCAST 2007

**Computer Aided
Systems
Theory**

EXTENDED ABSTRACTS

**11th International Conference on Computer Aided Systems Theory
Las Palmas de Gran Canaria, Spain, February 2007**

Preface

The concept of CAST as Computer Aided Systems Theory was introduced by F. Pichler in the late 80's to encompass those computer theoretical and practical developments as tools for problems in System Science. It was thought as the third component (the other two being CAD and CAM) that will provide for a complete picture of the path from Computer and Systems Sciences to practical developments in Science and Engineering.

Franz Pichler, of the University of Linz, organized the first CAST workshop in April 1988, which demonstrated the acceptance of the concepts by the scientific and technical community. Next, the University of Las Palmas de Gran Canaria joined the University of Linz to organize the first international meeting on CAST, (Las Palmas February 1989), under the name EUROCAST'89 and proved to be a very successful gathering of systems theorists, computer scientists and engineers from most of European countries, North America and Japan.

It was agreed that EUROCAST international conferences would be organized every two years, alternating between Las Palmas de Gran Canaria and a continental Europe location, being later decided to celebrate them in Las Palmas. Thus, successive EUROCAST meetings took place in Krems (1991), Las Palmas (1993), Innsbruck (1995), Las Palmas (1997), Vienna (1999), Las Palmas (2001), Las Palmas (2003) and Las Palmas (2005), in addition to an extra-European CAST Conference in Ottawa in 1994. Selected papers from those meetings were published by Springer-Verlag Lectures Notes in Computer Science nos. 410, 585, 763,1030, 1333, 1798, 2178, 2809, and 3643 and in several special issues of Cybernetics and Systems: an International Journal. EUROCAST and CAST meetings are definitely consolidated, as it is shown by the number and quality of the contributions over the years.

EUROCAST 2007, to be held in the Elder Museum of Science and Technology of Las Palmas, February 12-16, continues with the approach tested in last Conferences as an International computer related Conference with a true interdisciplinary character. There are different specialized Workshops which, in this occasion, are devoted to 1.- Systems Theory and Simulation, chaired by Pichler (Linz) and Moreno Díaz (Las Palmas); 2.- Computation and Simulation in Modelling Biological Systems, chaired by Rippicardi (Napoli); 3.- Intelligent Information Processing, chaired by Freire (A Coruña); 4.- Computers in Education, chaired by Martín-Rubio (Murcia); 5.- Grid Computing, chaired by Volkert (Linz); 6.- Applied Formal Verification, chaired by Bjers (Linz); 7.- Cellular Automata, chaired by Vollmar (Karlsruhe); 8.- Computer Vision, chaired by Álvarez (Las Palmas); 9.- Heuristic Problem Solving, chaired by Affenzeller (Hagenberg); 10.- Signal Processing Architectures, chaired by Huemer (Erlangen) and Müller-Wipperfurth (Hagenberg); 11.- Robotics and Robotic Soccer, chaired by Kopacek (Vienna); 12.- Cybercars and Intelligent Vehicles, chaired by Parent (Paris) and García-Rosa (Madrid) and 13.- Artificial Intelligence Components, chaired by Chaczko (Sidney).

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seated. The aim was to check the possibility to use some motion parameters for human identification.

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Real-Time Visual SLAM using a Single Wide-Angle Camera

Luis M. Bergasa, Rubén Chavarría, Rafael Barca, Elena López,
Manuel Ocaña, David Schleicher

Department of Electronics, University of Alcalá, Alcalá de Henares, 28805 Madrid, Spain
ruben_cht@yahoo.es, {bergasa, barca, elena, mocana}@depeca.uah.es

Abstract. This paper presents an improvement of the visual SLAM using a single wide-angle camera developed by Andrew Davison. Wide-angle cameras improve SLAM algorithm performance because mapped features are visible for larger camera motion, a wider range of camera movements is possible and features with very different view angle are simultaneously visible. In order to work with these cameras it is necessary to eliminate the lens distortion. We present a projection model with five distortion parameters instead the Davison model that uses only one.

Keywords: SLAM, single camera, wide-angle vision, real-time.

Introduction

Real-time Simultaneous Localization And Mapping (SLAM) methods have been achieved in the last years using different sensors: laser, sonar, cameras, etc. Some of them use stereo vision ([1], [2]). However, recent works have achieved real-time SLAM using a single camera [3]. Monocular vision adds a new challenge to the SLAM problem because of difficulty of determining 3D coordinates with a single image. Narrow field of view cameras have been used in most of these works.

Our proposal is based on the Davison work [3] who has achieved a real-time SLAM with a single camera. In later works, he proves that the use of wide-angle cameras improves the SLAM performance [4]. Perspective projection models are not accurate enough for wide-angle cameras, reason why it is necessary to use in addition a distortion model that improves the projections made by the previous one.

We use a projection model based on the camera calibration toolbox for Matlab [5][6]. The greater difference with the Davison model is that our model uses five coefficients to manage distortion (radial and tangential) instead one.

Implementation

In this paper we present a SLAM application for a single wide-angle camera based on the method developed by Davison. We use the camera calibration toolbox for Matlab [5][6].

than the one used by Davison. This model incorporates radial and tangential distortion to correct the deviation in the projected coordinates of the pixels.

Let P be a point in the space, and its coordinate vector, $X_W = [x_W \ y_W \ z_W]^T$, respecting the world reference frame. We obtain its coordinate vector respecting the camera reference frame, $X_C = [x_C \ y_C \ z_C]^T$, through this rigid motion model, $X_C = R \cdot X_W + T$, where R is the camera rotation matrix calculated from the camera orientation (more information can be found at [3] and [4]) and T is the camera position in the world reference frame. We project P on the image plane according to the intrinsic parameters: focal length (FC), principal point (CC), angle between x and y CCD sensor axes (α), radial distortion coefficients (K_{C1} , K_{C2} , K_{C3}) and tangential distortion coefficients (K_{C4} , K_{C5}).

First, we calculate the normalized image projection X_n :

$$X_n = \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -x_c / z_c \\ -y_c / z_c \end{bmatrix}$$

Before calculating the distortion factors we define r as $r^2 = x^2 + y^2$. Then, the radial distortion, d_r , which includes three distortion parameters, is calculated as:

$$d_r = 1 + K_{C1}r^2 + K_{C2}r^4 + K_{C3}r^6$$

The tangential distortion vector, d_t , includes the other two distortion parameters:

$$d_t = \begin{bmatrix} K_{C4}(r^2 + 2x^2) + 2K_{C5}xy \\ K_{C5}(r^2 + 2y^2) + 2K_{C4}xy \end{bmatrix}$$

The distorted image projection (X_d) is obtained from the normalized image projection (X_n) including lens distortion:

$$X_d = \begin{bmatrix} x_d \\ y_d \end{bmatrix} = d_r X_n + d_t$$

Finally, the pixel coordinates (u, v) are calculated from the normalized-distorted coordinates (x_d, y_d) through the linear following equation:

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} FC_u & \alpha FC_u & CC_u \\ 0 & FC_v & CC_v \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_d \\ y_d \\ 1 \end{bmatrix}$$

Where FC_u and FC_v are the camera focal length for u and v direction. CC_u and CC_v are the coordinates of the principal point, also known as the central point.

3 Results

For testing our projection model, we guided the camera through a well-known trajectory. This trajectory followed an "L" with a short arm 35cm long and a large arm 95cm long. The camera starts at 60cm from the origin in the world reference frame where a known template was located. Images of the trajectory were recorded to be processed off-line. These images allowed us to test the two projection models under the same conditions (camera velocity, camera shakes, etc).

Fig.1 shows the trajectory followed by the camera using the two projection models. Results obtained from our projection model are depicted in blue, results obtained from Davison projection model are in red and the ground truth of the camera trajectory in green. The top-left plot shows the 3D trajectory of the camera, and the top-right, bottom-left and bottom-right plots show the X, Y and Z projections of the trajectory respectively.

As can be seen the trajectory obtained from our model is more accurate than the obtained from the Davison one. Then, both models have similar processing time and can be executed on a regular PC with Linux in real-time.

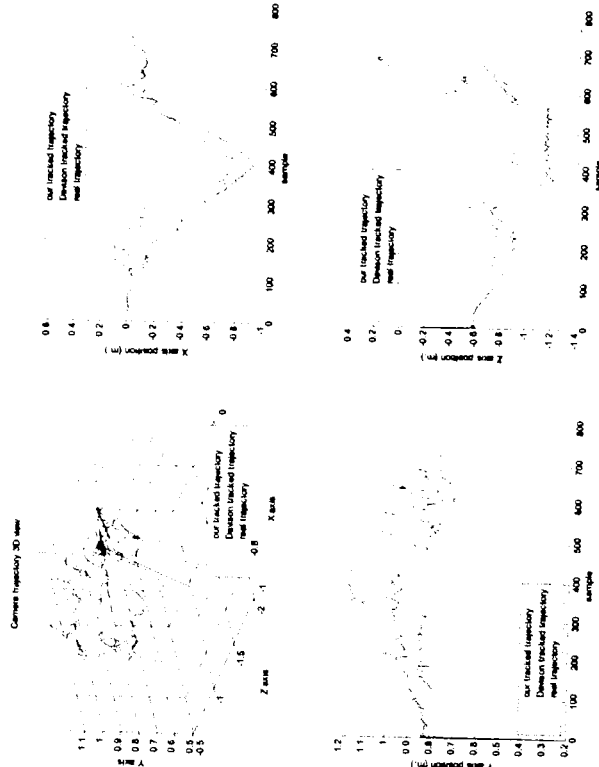


Fig.1. Tracked trajectories

Next figure shows three frames of the sequence used in the comparison. Features successfully projected and tracked are depicted in red, initialized features are in yellow and features not successfully projected are in blue. In figure 2.a the camera is 75cm from its initial position and the known template can be seen. In figure 2.b the

initial features are not seen. As can be seen in figure 2.c, the initial features are successfully recognized when the camera goes back towards its initial position.

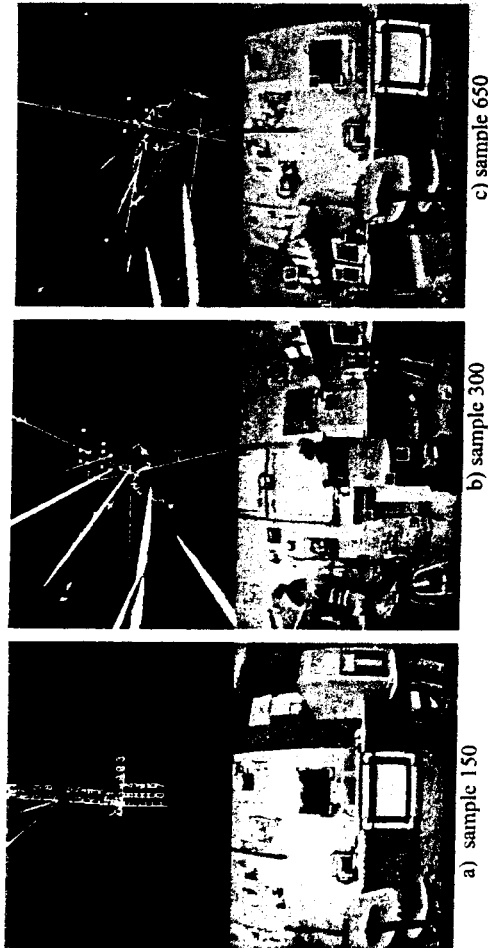


Fig. 2. Several frames during the test

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Real-Time Motion Detection from ALI Model

María T. López¹ Antonio Fernandez-Caballero¹, Miguel A. Fernández¹, José Mira², and Ana E. Delgado²

¹ Universidad de Castilla-La Mancha
 Instituto de Investigación en Informática (I3A) and
 Escuela Politécnica Superior de Albacete, 02071 - Albacete, Spain
 {mlopez,caballer,miki}@isi.uclm.es

² Universidad Nacional de Educación a Distancia
 E.T.S.I. Informática, 28040 - Madrid, Spain
 {jmira,adelgado}@dia.uned.es

In recent years, many researchers have explored the relation between discrete-time recurrent neural networks and finite state machines, either by showing their computational equivalence or by training them to perform as finite state recognizers from example [1]. An important issue in the motivation of this paper is that the performance of neural-based methods can be enhanced by encoding a priori knowledge about the problem directly into the networks [2]. This knowledge can be encoded into a recurrent neural network by means of finite state automata rules [3]. The second idea introduced is that such a finite state machine, implemented in hardware, may provide real-time performance. The algorithmic lateral inhibition (ALI) method [4],[5] is precisely inspired in the (recurrent and non-recurrent) neural computation mechanism known as lateral inhibition. This article shows how to implement the ALI method in motion detection by means of a formal model described as finite state machines, leading to an ALI module, and its further implementation in a programmable logic device, such as an FPGA.

The first aim of our proposal is to detect the temporal and local (pixel to pixel) contrasts of pairs of consecutive binarised images at a given gray level. We are in front of a vector quantization (scalar quantization) algorithm generally called multilevel thresholding. As well as segmentation in two gray level bands is a usual thing, here we are in front of a refinement to the segmentation in gray level bands.

In this step we have obtained the individual "opinion" of each computation element. But, our aim is also to consider the "opinions" of the neighbors. The aim of the next step is to focus on those pixels charged with an intermediate accumulated charge value, but directly or indirectly connected to saturated pixels by incrementing their charge. These "motion values" of the previous step constitute the input space, whereas the output is formed after dialogue processing with neighboring pixels by the so called permanency value.

Now, the aim of the last step is to obtain all moving patches present in the scene. The step considers the union of pixels that are physically together and at a same gray level band to be a component of an object. A set of recurrent lateral inhibition processes are performed to distribute the charge among all neighbors