Available online at www.sciencedirect.com
ScienceDirect
Expert Systems with Applications 33 (2007) 955–967
Expert Systems with Applications
www.elsevier.com/locate/eswa

Modelling the Stereovision-Correspondence-Analysis task by Lateral Inhibition in Accumulative Computation problem-solving method

Antonio Fernández-Caballero [a,*], María T. López [a], José Mira [b], Ana E. Delgado [b], José M. López-Valles [c], Miguel A. Fernández [a]

[a] Departamento de Sistemas Informáticos, Escuela Politécnica Superior de Albacete, and Instituto de Investigación en Informática de Albacete, Universidad de Castilla-La Mancha, 02071 Albacete, Spain
[b] Departamento de Inteligencia Artificial, E.T.S. Ingeniería Informática, Universidad Nacional de Educación a Distancia, 28040 Madrid, Spain
[c] Departamento de Telecomunicación, Escuela Universitaria Politécnica de Cuenca, Universidad de Castilla-La Mancha, 13071 Cuenca, Spain

Abstract

Recently, the Algorithmic Lateral Inhibition (ALI) method and the Accumulative Computation (AC) method have proven to be efficient in modelling at the knowledge level for general-motion-detection tasks in video sequences. More precisely, the task of persistent motion detection has been widely expressed by means of the AC method, whereas the ALI method has been used with the objective of moving objects detection, labelling and further tracking. This paper exploits the current knowledge of our research team on the mentioned problem-solving methods to model the Stereovision-Correspondence-Analysis (SCA) task. For this purpose, ALI and AC methods are combined into the Lateral Inhibition in Accumulative Computation (LIAC) method. The four basic subtasks, namely "LIAC 2D Charge-Memory Calculation", "LIAC 2D Charge-Disparity Analysis" and "LIAC 3D Charge-Memory Calculation" in our proposal of SCA are described in detail by inferential CommonKADS schemes. It is shown that the LIAC method may perfectly be used to solve a complex task based on motion information inherent to binocular video sequences.

Keywords: Algorithmic Lateral Inhibition; Accumulative Computation; Lateral Inhibition in Accumulative Computation; Stereovision; Correspondence analysis

1. Modelling the Stereovision-Correspondence-Analysis task

1.1. The Lateral Inhibition in Accumulative Computation method

Recently, the Algorithmic Lateral Inhibition (ALI) method, as well as the Accumulative Computation (AC) method, has proven to be greatly efficient in modelling at the knowledge level for general-motion-detection tasks in video sequences. More precisely, the task of persistent-motion detection has been widely expressed by means of the AC method (Mira, Fernández, López, Delgado, & Fernández-Caballero, 2003), whereas the ALI method has been used with the objective of moving-objects detection (Mira, Delgado, Fernández-Caballero, & Fernández, 2004), labelling and further tracking (López, Fernández-Caballero, Mira, Delgado, & Fernández, 2006). This paper exploits our research team current knowledge on the problem-solving methods mentioned to model the Stereovision-Correspondence-Analysis (SCA) task (López-Valles, Fernández, Fernández-Caballero, & Gómez, 2005). For this purpose, ALI and AC methods are combined into the Lateral Inhibition in Accumulative Computation (LIAC) method (Fernández-Caballero, Fernández, Mira, & Delgado, 2003) as a powerful problem-solving method

* Corresponding author. Tel.: +34 967 599200; fax: +34 967 599224.
E-mail address: caballer@info-ab.uclm.es (A. Fernández-Caballero).

0957-4174/$ - see front matter © 2006 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2006.07.009

(PSM) in generic computer vision motion-motivated tasks.

A complete description of the ALI method is available in Mira et al. (2004). In the non-recurrent ALI case, each calculation element samples its data in the central (C) and periphery (P) part of the volume that its RF (receptive field) specified in the input space V. On these two data fields, the calculation element carries out evaluation inferences and results comparison. This comparison inference is made according to a set of criteria to generate a set of discrepancy classes as input to the final selection, where the output is obtained from the set of outputs associated with the different discrepancy classes, according to the specific discrepancy classes generated by the previous comparison inference. In an analogous manner there is the inferential scheme for the recurrent ALI circuits. Now each element of calculus starts to infer from data sampled in the central (C^*) and periphery (P^*) parts of its feedback receptive fields in the output space. The values in C^* (individual opinion before dialogue) are compared with the evaluation of the "opinions" of all the elements in the periphery. This comparison is made according to a set of rules for consensus to produce a discrepancy class. Finally, as in the non-recurrent case, this discrepancy is the input to a selection to provide the consensus output.

The AC method is based on the permanency effect. Accumulative computation has now been largely applied to moving objects detection, classification and tracking in indefinite sequences of images (e.g. (Mira et al., 2003)). The more general modality of AC is the charge/discharge mode, which may be described by means of the following generic formula:

$$Ch(x,y,t) = \begin{cases} \min(Ch(x,y,t-1) + C, Ch_{\max}) & \text{if "}\textit{property } P(x,y,t)\text{"} \\ \max(Ch(x,y,t-1) - D, Ch_{\min}) & \text{otherwise} \end{cases} \quad (1)$$

This way, the temporal accumulation of the persistency of the binary property $P(x,y,t)$ measured at each time instant t at each pixel (x,y) of the data field is calculated. Generally, if the property is fulfilled at pixel (x,y), the charge value at that pixel $Ch(x,y,t)$ goes incrementing by increment charge value C up to reaching $Ch_{\max}$, whilst, if property P is not fulfilled, the charge value $Ch(x,y,t)$ goes decrementing by decrement charge value D down to $Ch_{\min}$. All pixels of the data field have charge values between the minimum charge, $Ch_{\min}$, and the maximum charge, $Ch_{\max}$. Obviously, values C, D, $Ch_{\min}$ and $Ch_{\max}$ are configurable depending on the different kinds of applications, giving rise to all different operating modes of the accumulative computation. Values of parameters C, D, $Ch_{\max}$ and $Ch_{\min}$ have to be fixed according to the applications characteristics. The particular values $Ch_{\max}$ and $Ch_{\min}$ have to be chosen by taking into account that charge values will always be between them. The value of C defines the charge increment interval between time instants $t-1$ and t. Greater values of C allow arriving in a quicker way to saturation. On the other hand, D defines the charge decrement interval between time instants $t-1$ and t. Thus, notice that the charge stores motion information as a quantified value, which may be used for several classification purposes. In (Mira et al., 2003) the architecture of the accumulative computation module is shown. Some of the operating modes may be noticed there, demonstrating their versatility and their computational power.

Lastly, the LIAC method, understood as the combination or fusion of the ALI and AC methods, consists precisely in using the accumulative computation (or permanency computation) mechanisms as the algorithmic part of the LI (lateral inhibition).

1.2. The Stereovision-Correspondence-Analysis task

In a conventional stereoscopic approach, usually two cameras are assembled with a horizontal distance between them. As a consequence, objects displaced in depth from the fixation point are projected onto image regions which are shifted with respect to the image centre. Brown, Burschka, and Hager (2003) describe in their work a great variety of algorithms that have been developed to analyze the depth in a scene in a survey article. In many previous works, a series of restrictions are used to approach the correspondence problem. The most usual restriction is the disparity one, which considers that is not likely that there are objects very close to the camera. The scene is usually limited to a medium distance. This way, too high disparities are eliminated (Sumi, Kawai, Yoshimi, & Tomita, 2002). Koenderink and van Doorn (1976) expressed the necessary theory in the best initial works related to disparity restriction, and Wildes (1991) implemented some of their ideas (Wilson & Knutsson, 1989). More recently, disparity in stereoscopy continues showing a great interest (e.g. Muhlmann, Maier, Hesser, & Manner, 2002; Gutiérrez & Marroquín, 2004).

According to the correspondence techniques used, we may classify methods into correlation-based, relaxation-based, gradient-based, and feature-based. The main correlation-based technique is the area-correlation technique (e.g. (Zabih & Woodfill, 1994)). Area-based approaches have the advantage of generating dense disparity maps directly. Matching elements for area-based methods are the individual pixels over which the matching cost is evaluated; pixel-to-pixel correspondence is assessed on image intensity function and similarity statistics. For instance, the work by Binaghi, Gallo, Marino, and Raspanti (2004) investigates the potential of neural adaptive learning to solve the correspondence problem within a two-frame adaptive area matching approach. The method is based on the use of the zero mean normalized cross-correlation coefficient integrated within a neural network model which uses a least-mean-square delta rule for training. Another approach (Di Stefano, Marchionnia, & Mattoccia, 2004) proposes an area-based stereo algorithm suitable to real time applications, where the core of the algorithm relies on the uniqueness constraint and on a matching process