Revisiting Algorithmic Lateral Inhibition and Accumulative Computation*

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Abstract. Certainly, one of the prominent ideas of Professor Mira was that it is absolutely mandatory to specify the mechanisms and/or processes underlying each task and inference mentioned in an architecture in order to make operational that architecture. The conjecture of the last fifteen years of joint research of Professor Mira and our team at University of Castilla-La Mancha has been that any bottom-up organization may be made operational using two biologically inspired methods called "algorithmic lateral inhibition", a generalization of lateral inhibition anatomical circuits, and "accumulative computation", a working memory related to the temporal evolution of the membrane potential. This paper is dedicated to the computational formulations of both methods, which have led to quite efficient solutions of problems related to motion-based computer vision.

1 Introduction

One of the most important problems in Artificial Intelligence (AI) and in Computational Neuroscience (CN) is to find effective calculation procedures that enable connecting the analytic models of the behavior of individual neurons, typical of the Neurodynamics [1], [2], with the formulations in natural language of the concepts and inferences associated to the high-level cognitive processes [23], [27], [28], [30]. Three years ago,the research community has celebrated the fiftieth anniversary of AI and it is evident that there is still no general and satisfactory solution to this problem, as clearly stated by Professor José Mira in one of his last papers [29]. The reasons for this lack of links between the models belonging to Physics and AI reside in the intrinsic complexity of the cognitive processes and in the lack of adequate methodological approaches.

The search for architectures of the cognition (the"logic of the mind") is a long-haul task with very limited results that has roots in the ancient Greece.

* This article is dedicated to the memory of our close master and friend, Professor José Mira.

J. Mira et al. (Eds.): IWINAC 2009, Part I, LNCS 5601, pp. 57–66, 2009.

Since then the task has essentially been of interest to philosophers, neurophysiologists, psychologists, mathematicians and, more recently, professionals of the field of computation in general and of Artificial Intelligence (AI) in particular. We are in front of a partial, fragmented and non-structured knowledge and look for an abstract structure that allows us to order adequately these pieces of knowledge. The architecture needs organization and structure, easy indexation and search and, finally, efficient use of this knowledge in inference and reasoning.

In the robotics field the name architecture is kept explicitly and such terms as "reactive", "situated" or "representational" are used to specify the organization of the software and hardware of an autonomous robot. In AI these organizational approaches are usually called paradigms and it is again distinguished between connectionist, situated, symbolic or representational and hybrid. In this work our architecture of hybrid character, which combines a bottom-up part of connectionist type with a top-down one of symbolic type is presented. To fix ideas we focus on the visual path but we also give out the conjecture of the potential validity in other sensory modalities and in the understanding and synthesis of other tasks in which reactive components are combined with others of intentional nature.

The ideas underlying the work are: (1) In order to theorize and to solve problems that go beyond the retinotopic projection step it is necessary to propose neurophysiologically plausible synthetic architectures (knowledge models), but without the precision by which the more peripheral structures are known. (2) It is not sufficient to model and interpret the neuronal function at physical (physiological) level of registrations of slow potentials or spikes trains. It is necessary to re-formulate the neuronal mechanisms at symbolic level in terms of inferential rules and frames, closer to the natural language used by an external observer when describing the visual processes, or when performing psychophysical experiments [13], [14].

2 Description of the Two Neural Processes

In order to make operational any architecture it is necessary to specify the mechanisms and/or processes underlying each subtask and inference mentioned in that architecture. The conjecture of our team is that any bottom-up organization may be made operational using two biologically inspired methods called (1) "algorithmic lateral inhibition" (ALI), a generalization of lateral inhibition (LI) anatomical circuits [3], and, (2) "accumulative computation" (AC). Firstly, ALI is considered in the following section and AC in the next one.

2.1 Algorithmic Lateral Inhibition

Lateral Inhibition at the Physical Level. There are some neuronal structures that are repeated at all the integration levels in the nervous system and that emerge again in the global behavior of human beings. This leads us to

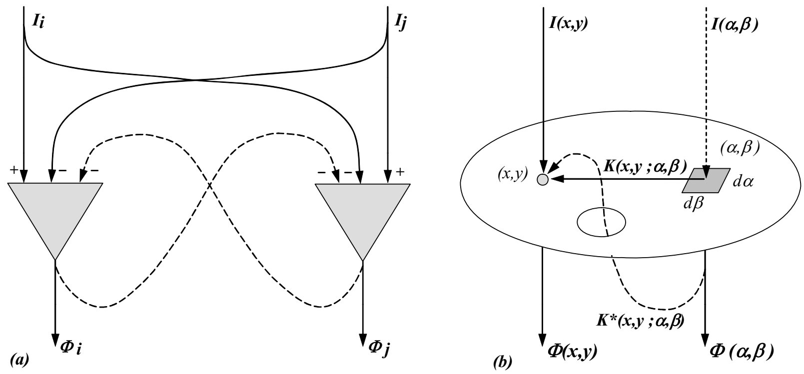

Fig. 1. Non-recursive (continuous line) and recursive (discontinuous line) LI connectivity schemes at the physical level. (a) Discrete case. (b) Continuous case.

think that they have endured the evolution process because they were adaptively useful for interacting with the environment. If we look at these structures from an electronic and computational perspective we could say that they are the "basic functional modules" in terms of which evolution has designed the best architecture for the nervous system (NS) to process information. This is the case of the lateral inhibition circuits, due to the wide range of functions which they may synthesize, to their capacity of explaining in neurophysiology, and their facility of abstraction when accepting to maintain invariant their structure in front of semantic level changes.

LI schemes may be found in levels such as neurogenesis, dendro-dendritic contacts, neuronal circuits in the retina, lateral geniculate body and in cerebral cortex, in the interaction between groups of neurons (ocular and orientation dominance columns) [24]. At the physical level, in terms of interconnected circuits that are described using a language of signals, there are two basic connectivity schemes: (1) non-recursive LI, and (2) recursive LI, with feedback (as outlined in Fig. 1). In non-recursive LI, the modification of a unit response depends on the inputs to the neighboring units, and in recurrent LI it depends on the outputs of the neighboring units.

If extending the formulation to the continuous case, (Fig. 1), the terms of interaction become nuclei of a convolution integral, so that the output, $\Phi(x,y)$, is the result of accumulating the direct excitation of each unit, $I(x,y)$, with the inhibition from modulating the excitation received by the connected neighboring units, $I(\alpha,\beta)$,via the weight factors $K(x,y;\alpha,\beta)$. The difference nucleus, $K(x,y;\alpha,\beta)$, is now responsible for the specific form of the calculation which, in all cases, acts as a detector of contrasts. In the recursive LI , it is the direct output, $\Phi(x,y)$, which accumulates the inhibition from the responses of the neighboring units, $\Phi(\alpha,\beta)$, weighted by an interaction coefficient $K^*(x,y;\alpha,\beta)$, basically different from that of the direct path (K).

Here again, in recursive LI, the shape and size of the receptive field (the interaction nucleus K^*) specifies the network connectivity (cooperation-competition area) and the calculation details (syntony, orientations, shapes, speeds, and so on). The most usual shape in K and K^* is obtained from subtracting two Gaussians. Thus the calculation structures inherent in the entire LI network are obtained: (1) a central area (ON or OFF), (2) a peripheral area (OFF or ON), and, (3) an excluded region (outside the receptive field).

Algorithmic Lateral Inhibition at Symbol Level. The LI model at the physical level is limited to a language of physical signals as functions of time. The first possible abstraction, which passes from a circuit to an algorithm, is obtained by rewriting the accumulation and inhibition processes in terms of rules (conditionals "if-then"), as a generalization of the weighted sum and the threshold. The condition field of a rule generalizes the weighted sum and the conditional generalizes the non-linearity of the threshold. Furthermore, the structure of the LI model is maintained. In other words, now also receptive fields (data fields in a FIFO memory) with an excitatory center and an inhibitory periphery, both for the input space (non-recursive LI) and for the output space (recursive IL) are defined. However, the nature of these input and output spaces is changed drastically, to be spaces of representation; that is, they are multidimensional spaces, where each "axis" represents possible values of an independent variable which measure an independent possible property of inputs and outputs. For the input space, the properties are those pertinent to the description of the external and internal "world", as seen by the previous neural nets. For the output space, properties are "decisions" of the net under consideration in the proper time axis. In the simplest case, the axons of each neuron of the net are proposing a sequence of "decisions" that fill in the output FIFO memory. Additionally, the decision rules in ALI need not be limited to analytic but can include also logical-relational operators as components of the calculus carried out by its condition fields [3], [24].

With this interpretation of ALI, each element of calculus samples its data in the center and periphery of the volume specified by its receptive field in the input space, and also samples in the center and periphery of the volume which specifies its receptive field in the output space. By specifying the nature of the decision rules the different types of calculus attainable by a network of algorithmic lateral inhibition (ALI) are obtained.

Algorithmic Lateral Inhibition as a Method at Knowledge Level. To complete the possibilities of the LI network, we do a new abstraction process and we pass from the symbol level to the knowledge level by generalizing the rules in terms of inferences [4], [24]. Through this abstraction process it is possible to consider ALI circuits as the anatomical support of an inferential scheme (Fig. 2).

2.2 Accumulative Computation

Usually the time evolution of the neuron membrane potential is modeled by a first order differential equation known as the "leaky integrator model". If we

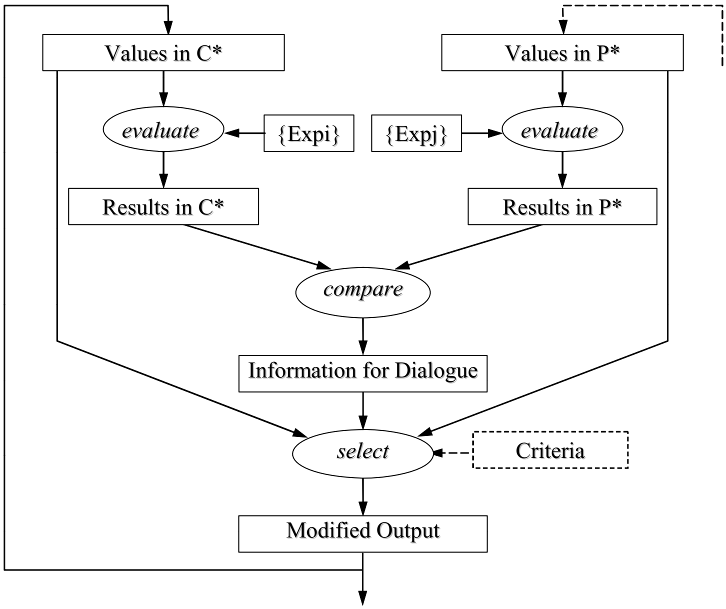

Fig. 2. Recurrent ALI inferential scheme. The results of the evaluation in the central (C*) and peripheral (P*) parts of the feedback receptive field are first compared and the result of this comparison is used to select the updated output.

move from differential equations to equations in finite differences then we get the temporal ALI model previously described, in which each element of calculus samples its input and feedback data from two FIFO memories. A different way of modeling time evolution of membrane potential is consider the membrane as a local working memory in which neither the triggering conditions nor the way in which the potential tries to return to its input-free equilibrium value, needs to be restricted to thresholds and exponential increases and decays. This type of working memory was named "accumulative computation" (AC), [5], [6], [25] and is characterized by the possibility of controlling its charge and discharge dynamics in terms of:

1. The presence of specific spatio-temporal features with values over a certain threshold.
2. The persistency in the presence of these features.
3. The increment or decrement values ($\pm\delta Q$) in the accumulated state of activity of each feature and the corresponding current value, $Q(t)$.
4. The control and learning mechanisms.

The upper part of Fig. 3 shows the accumulative computation model's block diagram. The model works in two time scales, a macroscopic, t, associated to the external data sequence to be processed by the net and a microscopic one, τ,

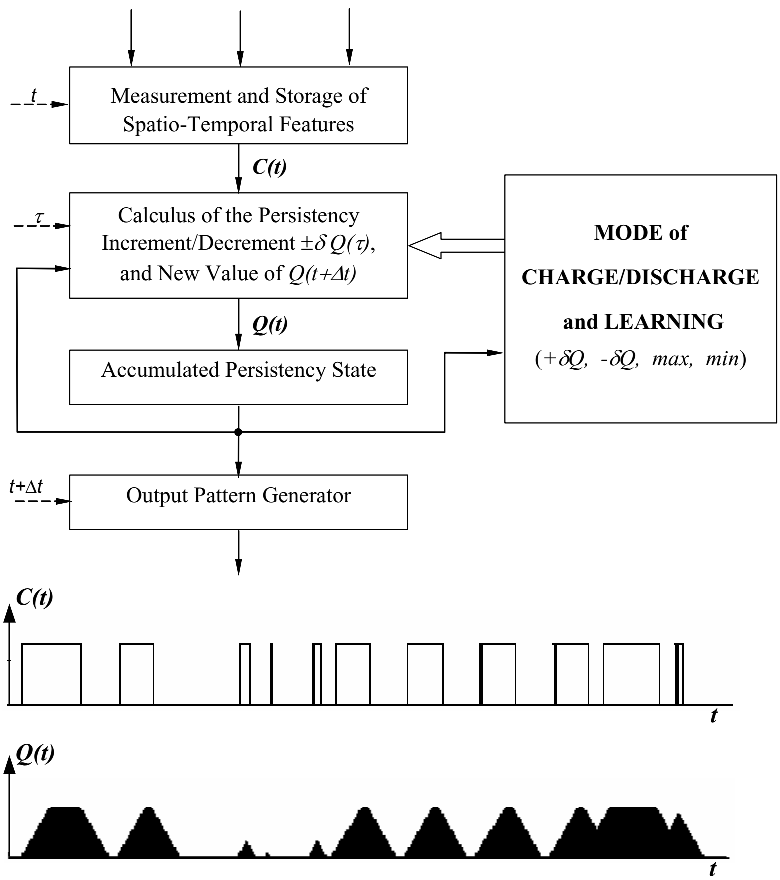

Fig. 3. The AC working memory model (upper part) and an example of the temporal evolution of the accumulated persistency state, Q(t), in response to an specific sequence of values of a detected feature, C(t), (lower part)

associated to the set of internal processes that take place while the external data (an image, for instance) remain constant. The lower part of Fig. 3 illustrates the temporal evolution of the state of the charge in an AC working memory in front of a particular one-dimensional stimuli sequence.

The control rules used to calculate the persistency of motion through time are:

$$Q[x,y;t+\Delta t] = \begin{cases} \max(Q[x,y;t] - \delta Q, min), \text{ if } C[x,y;t] = 1 \\ \min(Q[x,y;t] + \delta Q, max), \text{ otherwise} \end{cases} \quad (1)$$

where $C[x,y;t] = 1$ means that motion has been detected on pixel $[x,y]$ at t.

3 Applications in Computer Vision

In this paper we have re-explored the fact that with only two synthetic mechanisms, ALI and AC, it is sufficient to do computational an important part of visual processes. Some of the works of our group support the validity of this methodological approximation, as described in this section.

Firstly, AC was applied to the problem of the classification of moving objects in long image sequences [5], showing its capacity to be implemented in real-time [7]. Later on the combination of AC and ALI was used in the resolution of the problem of segmenting moving silhouettes in video sequences [8], [9]. Its neuronal nature was described in detail [10], as well as the model for motion detection [11] and the influence of each parameter of the combination between AC and ALI [12]. In all these papers the novel model based in neural networks combining AC and ALI was denominated "lateral interaction in accumulative computation" (LIAC) [11].

From the good results obtained by means of these methods in computer-vision-based motion analysis, the following step was the challenge of facing selective visual attention (dynamic) by means of a research line [15], [16] where the importance of the incorporation of new parameters appeared. This research aims in describing a method for visual surveillance based on biologically motivated dynamic visual attention in video image sequences. The system is based on the extraction and integration of local (pixels and spots) as well as global (objects) features. Our approach defines a method for the generation of an active attention focus on a dynamic scene for surveillance purposes. The system segments in accordance with a set of predefined features, including gray level, motion and shape features, giving raise to two classes of objects: vehicle and pedestrian. The solution proposed to the selective visual attention problem consists of decomposing the input images of an indefinite sequence of images into its moving objects, defining which of these elements are of the user's interest at a given moment, and keeping attention on those elements through time. Features extraction and integration are solved precisely by incorporating the mechanisms described, AC and ALI.

Among others, we also introduced velocity to improve the capture of the attention on the objects in movement [17]. In this case, we highlight the importance of the motion features present in our algorithms in the task of refining and/or enhancing scene segmentation in the methods proposed. The estimation of these motion parameters is performed at each pixel of the input image by means of the AC method. "Motion presence", "module of the velocity" and "angle of the velocity", all obtained from AC computation method, are shown to be very significant to adjust different scene segmentation outputs in our dynamic visual attention method [18], [19].

In parallel with the previous works, again mainly AC was used, and ALI in a minor degree, to improve the segmentation of moving objects, by introducing stereovision, with the purpose of adding a parameter that can contribute enormously in any tracking task in the three-dimensional world; this is parameter depth [20]. In this work a method that turns around the existing symbiosis between stereovision and motion is used; motion minimizes correspondence ambiguities, and stereovision enhances motion information. The central idea behind our approach is to transpose the spatially-defined problem of disparity estimation into the spatial-temporal domain. Motion is analyzed in the original sequences by means of AC and the disparities are calculated from the resulting two-dimensional motion charge maps [22].

To date the first results applied to the potential usefulness in mobile robotics have also been introduced [21]. Finally, the LI model at the knowledge level, the so-called ALI [26], seems to be a promising method to solve problems of cooperation and dialogue in the theory of multi-agent systems.

4 Conclusions

Neurally-inspired computer vision involves at least memory processes, alert, surveillance, selective attention, divided attention, reinforcement learning, intentionality and conscience. The complexity of these mechanisms is the reason for the difficulty found when trying to synthesize them computationally. A satisfactory solution, close to biology, is still a long term objective.

In this work we have revisited the works of the joint research of Professors José Mira and Ana E. Delgado with our team in computer vision by using a description framework based in the use of two basic neuronal mechanisms, the lateral inhibition and the working memory related to the temporal evolution of the membrane potential, which was denominated accumulative computation. In order to extract the maximum performance the two mechanisms at the three levels used in Artificial Intelligence to describe a calculation (the physical level, the level of the symbols and the knowledge level) have been formulated. We have proposed a method to interpret the function performed by a neural circuit, not only at the level of neurophysiologic signals but also in terms of symbolic rules and inferential schemes.

In the previous section, we have also commented some of the results obtained by the research team from using the conceptual scheme described in the previous sections. These results although reasonable in AI, are far away from approaching biological solutions for at least two reasons. The first one is the enormous constituent difference between biological systems and synthesis elements used in computer vision. The second reason is the ignorance on the architectures of cognition, starting from the doubt on the suitability of the term architecture to describe perception in humans.

Nevertheless, when seeking to construct solutions able to be computed with programs, cameras and robots, there is no other way than trying to equip the knowledge that we have on the biological solution to the problem of attention with structure and organization. Anything that we can not describe in a structured, declarative, clear, precise and formal way is not computable. That is why we think that our approach of firstly looking into neuroscience as an inspiration source, then proposing real computational models, and at the same time evaluating its efficiency in problem solving, independently of its biological origin, is useful.

Acknowledgements

This work was partially supported by the Spanish Ministerio de Ciencia e Innovación under project TIN2007-67586-C02-02, and by the Spanish Junta de Comunidades de Castilla-La Mancha under projects PII2I09-0069-0994, PII2I09-0071-3947 and PEII09-0054-9581.

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