PARALLEL AND SERIAL CONTROL STRATEGIES OF IMAGE UNDERSTANDING

Shikha Arya[1], Arti Mishra[2], Meenakshi Pathak[3], Vandana[4]

[1,2,3,4]*Assistant Professor, CS Department, SRMSWCET, Bareilly, (India)*

ABSTRACT

Many image processing tasks exhibit a high degree of data locality and parallelism and map quite readily to specialized massively parallel computing hardware. Parallel distribution of image file reduces the complexity and increase the capability of image enhancement. Image understanding and computer vision are two closely related multidisciplinary research fields concerned with the use of computer algorithms to modify or analyze digital images using signal and image processing, machine learning, and artificial intelligence techniques in order to achieve certain tasks or applications. One of the main goals of image understanding and computer vision is to duplicate the abilities of human vision by electronically perceiving and understanding an image. Image understanding algorithms are required to solve more practical applications. In this paper we represent serial parallel control strategies to handle digital images in a optimized way.

Keywords: Parallel Processing Control, Serial Processing Control, Bottom Up Strategy, Top Down Strategy, Hierarchal And Non-Hierarchal Combined Control.

I. INTRODUCTION

Image understanding can be achieved only as a result of cooperation of complex information processing tasks and appropriate control of these tasks. Biological systems include a very complicated and complex control strategy incorporating parallel processing, dynamic sensing sub-system allocation, behavior modifications, interrupt-driven shifts of attention, etc. As in other AI problems, the main goal of computer vision is to achieve machine behavior similar to that of biological systems by applying technically available procedures Parallel and serial processing control: Both parallel and serial approaches can be applied to image processing, although sometimes it is not obvious which steps should be processed in parallel and which serially. Parallel processing makes several computations simultaneously (e.g., several image parts can be processed simultaneously), and an extremely important consideration is the synchronization of processing actions that is, the decision of when, or if, the processing should' wait for other processing steps to be completed.

II. HIERARCHICAL CONTROL

Image information is stored in different representations during processing. The image processing is being controlled by the image data information or by higher-level knowledge according to these different approaches as:

2.1 Control by the Image Data (Bottom-up Control)

Processing proceeds from the raster image to segmented image, to region (object) description, and to their recognition.

2.2 Model-Based Control (Top-Down Control)

A set of assumptions and expected properties is constructed from applicable knowledge. The satisfaction of those properties is tested in image representations at different processing levels in a top-down direction, down to the original image data. The image understanding is internal model verification, and the model is either accepted or rejected. The two basic control strategies do not differ in the types of operation applied, but do differ in the sequence of their application, in the application either to all image data or just to selected image data, etc. The control mechanism chosen is not only a route to the processing goal; it influences the whole control strategy. Neither top-down nor bottom-up control strategies can explain the vision process or solve complex vision sensing problems in their standard forms. However, their appropriate combination can yield a more flexible and powerful vision control strategy.

2.3 Bottom-Up Control: Algorithm 1: Bottom-Up Controls Have Following Steps

2.3.1 Pre-processing: Transform the raster image data (pre-process the image) to highlight information that may be useful in further processing steps. Appropriate transformations are applied throughout the image.

2.3.2. Segmentation: Detect and segment image regions that can correspond to real objects or object parts.

2.3.3. Understanding: If region descriptions were not used in step 2,

We determine an appropriate description for regions found in the segmented image. Compare the detected objects with real objects that are present in the solution domain (i.e. using pattern recognition techniques). It is obvious that the bottom-up control strategy is based on the construction of data structures for the processing steps that follow. Note that each algorithm step can consist of several sub steps however, the image representation remains unchanged in the sub steps.

The bottom-up control strategy is advantageous if a simple and efficient processing method is available that is independent of the image data content. Bottom-up control yields good results if unambiguous data are processed and if the processing gives reliable and precise representations for later processing steps. The recognition of well-illuminated objects in robotic applications is an example-in this case, bottom-up control results in fast. If the input data are of low quality, bottom-up control can yield good results only if unreliability of the data. This implies that the main image understanding role must be played by a control strategy that is not only a concatenation of processing operations in the bottom-up direction, but that also uses internal model goal specifications, planning, and complex cognitive processes.

A good example of a bottom-up control strategy is Marr's image understanding approach [4]. The processing begins with a two-dimensional intensity image and tries to achieve a three-dimensional image understanding through a sequence of intermediate image representations. Marr's understanding strategy is based on a pure bottom-up data flow using only very general assumptions about the objects to be identified.

2.4 Model-Based Control

There is no general form of top-down control as was presented in the bottom-up control algorithm. The main top-down control principle is the construction of an internal model and its verification, meaning that the main principle is goal-oriented processing. Goals at higher processing levels are split into sub-goals at lower processing levels, which are split again into sub-goals etc., until the sub-goals can be either accepted or rejected directly.

An example will illustrate this principle. Imagine that you are in a large hotel, and your spouse parked your white Volkswagen Beetle somewhere in the large parking lot in front of the hotel. You are trying to find your car, looking from the hotel room window. The first-level goal is to find the parking lot. A sub-goal might be to detect all white cars in the parking lot and to decide which of those white cars Volkswagen Beetles are. All the given goals can be fulfilled by looking from the window and using general models (general knowledge) of cars, colors, and Beetles. If all the former goals are fulfilled, the last goal is to decide if the detected white Volkswagen Beetle really is your car and not some other white Beetle; to satisfy this goal, specific knowledge of your car is necessary. You have to know what makes your car special-the differences between your car and others. If the test of the specific properties of the detected car is successful, the car is accepted as yours; the model you built for your white Beetle is accepted, the car is located, and the search is over. If the test of specific properties is not successful, you have to resume testing at some higher level, for instance, to detect another, as yet untested white Volkswagen Beetle.

The general mechanism of top-down control is hypothesis generation and its testing. The internal model generator predicts what a specific part of the model must look like in lower image representations. The image understanding process consists of sequential hypothesis generation and testing. The internal model is updated during the processing according to the results of the hypothesis tests. The hypothesis testing relies on a (relatively small) amount of information acquired from lower representation levels, and the processing control is based on the fact that just the necessary image processing is required to test each hypothesis. The model-based control strategy seems to be a way of solving computer vision tasks by avoiding brute-force processing; at the same time, it does not mean that parallel processing should not be applied whenever possible Image. This is especially true in modeling natural objects-human faces together with their mimics serve as a good example. Physical modeling is another branch of computer vision and image understanding [5] in which four main techniques appear: reflection models for vision; relations between shape and reflection, statistical and stochastic modeling, and modeling deformable shapes (elastics in vision) .Clearly, all these techniques may significantly increase the knowledge available in the image understanding process. From the point of view of the context being discussed here, deformable models of non-rigid objects seem to widen substantially the rank of feasible applications. Sections 10.3 and 10.4 discuss the application of deformable statistical models to representation and analysis of 2D, 3D, and 4D image data.

III. COMBINED CONTROL

Combined control mechanisms that use both data- and model-driven control strategies are widely used in modern vision applications, and usually give better results than any of the previously discussed, separately applied, basic control strategies. Higher-level information is used to make the lower-level processing easier, but alone is insufficient to solve the task. Seeking cars in aerial or satellite image data is a good example; data-driven control is necessary to find the cars, but at the same time, higher-level knowledge can be used to simplify the problem since cars appear as rectangular objects of specific size, and the highest probability of their appearance is on roads.

An example of a robust approach to automated coronary border detection in angiographic images illustrates the combined control strategy. X-ray images are acquired after injecting a radio-opaque dye into the arteries of a human heart.. Unfortunately, the bottom-up graph search often fails in more complicated images, in the presence of closely parallel, branching, or overlapping vessels, and in low-quality images. Image data representing such a difficult case are shown in Fig 1 together with the result of the bottom-up graph search (the same method that worked so well for a single-vessel case). To achieve reliable border detection in difficult images, a hybrid control strategy was designed combining bottom-up and top-down control steps; the following principles are incorporated in the process.

3.1. Model-based Approach: The model favors symmetric left and right borders as those most typical in coronary imagery.

3.2. Hypothesize and Verify Approach: Based on multi-resolution processing, the approximate vessel border is detected at low resolution and the precision is increased at full resolution (also, multi-resolution speed up the border detection process).

3.3. A Prior Knowledge: Knowledge about directions of edges forming the vessel border is used to modify a graph search cost function.

3.4. Multi-Stage Approach: Models of different strength are applied throughout the processing.

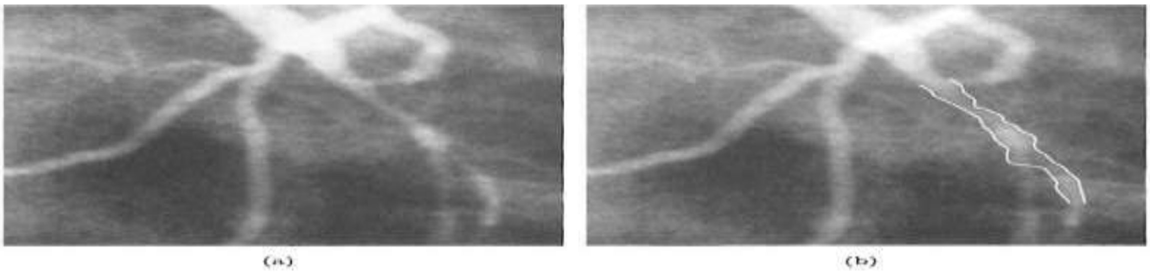

Fig. 1: Coronary Angiogram. (A) Original X-Ray Image. (B) Borders Detected By A Bottom-Up Graph Search Approach. Note The Incorrect Border At The Bifurcation.

The method searches for left and right coronary borders simultaneously, performing a three-dimensional graph search and the border symmetry model is thus incorporated in the search process. The three-dimensional graph results from combining two conventional edge detection graphs of the left and the right coronary borders .The model guides the search in regions of poor data, and where the image data have an acceptable quality, the search is guided by the image data. A frequent problem of model-based control strategy is that the model control necessary in some parts of the image is too strong in other parts (the symmetry requirements of the model have a larger influence on the final border than Ii non-symmetric reality), corrupting the border detection results. This is the rationale for a multi-stage approach where a strong model is applied at low resolution, and a weaker model leaves enough freedom for the search to be guided predominantly by image data at full-resolution, thereby achieving higher overall accuracy. Nevertheless, the low-resolution coronary borders detected by cooperation with the model guarantee that the full-resolution search will not get lost--the low-resolution border is used as a model border in the full-resolution search. A block algorithm of the control steps is now given, accompanied by a label showing whether the particular step is done in a bottom-up or top-down manner.

Algorithm 2: Coronary border detection-a combined control strategy

2.1. (top-down) Detect a vessel centerline in interaction with an operator (show which vessel is to be processed), and straighten the vessel image, Fig. 2a, 2b.

2.2. (Bottom-up) Detect image edges in full resolution, Fig. 2c.

2.3. (Bottom-up) Detect local edge directions in the straightened intensity image, Fig. 2d.

Fig. 2: Steps of coronary border detection (I). (a) Centerline definition. (b) Straightened image data. (c) Edge detection. (d) Edge direction detection

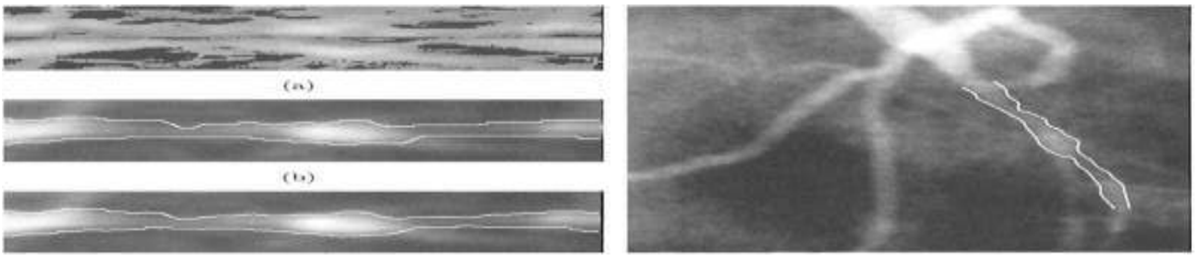

Fig. 3: Steps of coronary border detection (II). (a) Modified cost function-note that the cost increases in non-probable border locations image areas, where edge direction does not support location of the border. (b) Approximate coronary borders acquired in low resolution. (c) Precise full-resolution border in straightened image. (d) Full-resolution coronary borders in original image data.

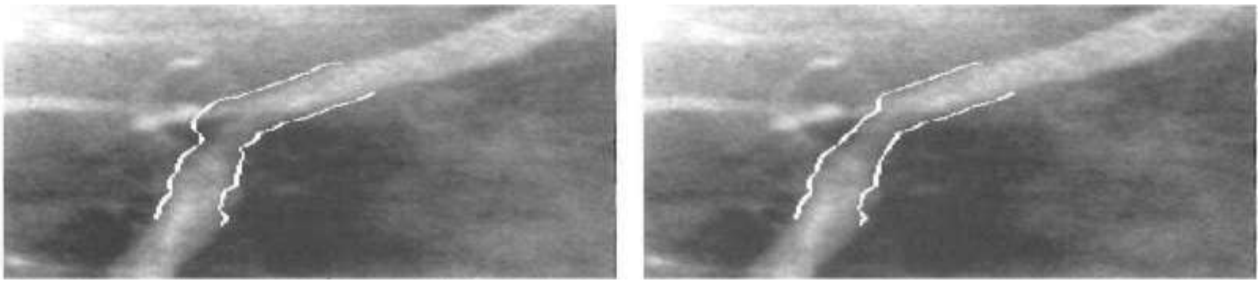

Fig. 4: Coronary border detection. (a) Borders resulting from the pure bottom-up graph search approach follow borders of the vessel branch. (b) Results of the combined control graph search strategy follow the coronary borders correctly.

2.4. (top-down) Modify the cost matrix using a. prior knowledge about edge directions and the directional edge image, Fig. 3a

2.5. (bottom-up) Construct a low-resolution image and a low-resolution cost matrix.

2.6. (Top-down) Search for the low-resolution pair of approximate borders using the vessel symmetry model Fig. 3b.

2.7. (top-down) Find an accurate position of the full-resolution border using the low resolution border as a model to guide the full resolution search, Fig. 3c. The symmetry model is much weaker than in the low resolution search.

2.8. (bottom-up) Transform the results from the straightened image to the original image, Fig. 3d.

2.9. (top-down) Evaluate the coronary disease severity.

Results of this strategy applied to coronary vessel data are given in Fig. 4. It is obvious that a combined control strategy can improve processing efficiency. Further, some of the steps are not sequential ill principle (such as edge image construction) and can be computed in parallel.

IV. NON-HIERARCHICAL CONTROL

There is always an upper and a lower level in hierarchical control. Conversely, nonhierarchical control can be seen as a cooperation of competing experts at the same level. Non-hierarchical control can be applied to problems that can be separated into a number of sub-problems, each of which requires some expertise. The order in which the expertise should be deployed is not fixed. The basic idea of non-hierarchical control is to ask for assistance from the expert that can help most to obtain the final solution. The chosen expert may be known, for instance, for high reliability, high efficiency, or for the ability to provide the most information under given conditions. Criteria for selection of an expert from the set may differ; one possibility is to let the experts calculate their own abilities to contribute to the solution in particular cases-the choice is based on these local and individual evaluations. Another option is to assign a fixed evaluation to each expert beforehand and help is then requested from the expert with the highest evaluation under given conditions. The criterion for expert choice may be based on some appropriate combination of empirically detected evaluations computed by experts, and evaluations dependent on the actual state of the problem solution. Non-hierarchical control strategies can be illustrated by the following algorithm outline.

Algorithm 3: Non-Hierarchical Control

3. l. Based on the actual state and acquired information about the solved problem, decide on the best action, and execute it.

3.2. Use the results of the last action to increase the amount of acquired information about the problem.

3.3. If the goals of the task are met, stop. Otherwise, return to step l.

A system for analysis of complex aerial photographs [6] is an example of a successful application of non-hierarchical control--the blackboard principle was used for competing experts. To explain the main idea of a blackboard, imagine a classroom full of experts. If any of them wants to share knowledge or observations with others, a note is made on the blackboard. Therefore, all others can see the results and use them. A blackboard is a specific data structure that can be accessed by all the experts and is a data structure first used in speech recognition-computer vision applications followed [3]. The blackboard usually includes a mechanism that retrieves specialized sub-systems which can immediately affect the standard control. These sub-systems are very powerful and are called daemons. The blackboard must include a mechanism that synchronizes the daemon activity. Programming with daemons is not easy, and the design of daemon behavior is based on general knowledge of the problem domain. Therefore, the programmer can never be absolutely sure if the daemon procedure based on some specific property will be activated or not; moreover, there is no guarantee that the daemon will be activated in the correct way. To limit the uncertainty of daemon behavior, the following additional rules are usually added.

• The blackboard represents a continuously updated part of the internal model that corresponds to image data

• The blackboard includes a set of rules that specify which daemon sub-system should be used in specific cases.

The blackboard is sometimes called the short-term memory-it contains information about interpretation of the processed image. The long-term memory, the knowledge base, consists of more general information that is valid for (almost) all representations of the problems to be solved [3]; all the information about a specific image is stored in the blackboard (segmented region properties and their relations). The blackboard can activate 13 sub-systems of region detection, all of which communicate with the blackboard in a standard way, and the only way the sub-systems can communicate with each other is via the blackboard. The blackboard data structure depends on the application; in this particular case, the structure takes advantage of a priori global knowledge of the domain such as the physical size of pixels, the direction of the sun, etc. Additionally, the blackboard maintains a property table in which all the observations on image regions is stored, together with the information about the region class (resulting from recognition) . An integral part of the blackboard is represented by the symbolic region image that provides information about relations between regions. The primary aim of the blackboard system is to identify places of interest in the image that should be processed with higher accuracy, to locate places with a high probability of a target region being present.

The approximate region borders are found first, based on a fast computation of just a few basic characteristics--saving computational time and making the detailed analysis easier. By using the information that comes from the region detection sub-systems via the blackboard. The blackboard serves as a place where all the conflicts between region labeling are solved (one region can be marked by two or more region detection sub-systems at the same time and it is necessary to decide which label is the best one). Furthermore, the labeling errors are detected in the blackboard, and are corrected using back-tracking principles.

V. CONCLUSION

The principal image understanding control strategies have been presented here was noted that a wide variety of knowledge representation techniques, object description methods, and processing strategies must co-exist in any image understanding system. The role of knowledge and control is reviewed in [2]_within the context of image and speech understanding systems [1], [3]. Image understanding approaches following a bottom-up control strategy and allowing the use of semantic networks are helpful for better understanding of images and knowledge-based composition of image interpretation processes is discussed . Machine learning strategies for image understanding, neural networks and fuzzy logic are increasingly play a important and role for better understanding of images in parallel processing which is the future of control strategies.

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