Pipeline Implementation of New Segmentation Based on Cognate Neighborhood Approach

V.Vijaya Kumar, A. Nagaraja Rao, U.S.N.Raju, and B.Eswara Reddy

Abstract—**In this paper, we cast the segmentation problem as the maximization of cognate information between the row and column pairs of the neighborhood. For this, the maximum and minimum gradient on pairs of row and column of the local neighborhood are calculated and applied on the original image. The maximum and minimum row and column pair of the local neighborhood forms the contribution of primitive morphological operations, dilation and erosion respectively. For extracting strong edges edge increase and edge decrease are applied on local neighborhood. The final segmentation is obtained after applying the above preprocessing steps by using a new approach of cognate neighborhood. To test the above process of segmentation the method is applied on brodatz textures, leena and brain MRI images, which resulted a good segmentation**.

Index Terms— **Dilation, Erosion, Edge Increase, Edge Decrease, Morphology, Row and Column Pairs.**

I. Introduction

Texture segmentation is carried out by many researchers in different ways. There are two approaches to the segmentation of the images: edge-based and region-based approaches. The edge-based method [1] extracts the boundary of the object by measuring the amount of defocus at each edge pixel. The algorithm demonstrated high accuracy for segmenting man-made objects and objects with clear boundary edges. The region-based segmentation algorithms in [2], [3], [4] rely on the detection of the high frequency areas in the image. A reasonable starting point is to measure the degree of focus for each pixel by computing high-frequency components. Nonetheless, if the focused smooth region is too large, the proposed algorithm may need to incorporate some semantic or human knowledge. Recently Junmo Kim et al. proposed a new information-theoretic approach [5] to image segmentation using nonparametric statistical method.

Boundary functional was first proposed by Kass et al. [6] and geodesic active contours by Caselles et al. [7], [8] for active contour segmentation. Region based active contours were first introduced by Ronfard et al. [9] and Cohen et al. [10]. Chakraborty et al. [11] combined both boundary and region information for medical images segmentation. Then Chesnaud et al.[12], Chan et al. [13], Zhu et al.[14], Paragios et al. [15], and Debreuve et al. [16] introduced region based static descriptors for image segmentation. Jehan-Besson et al [17] address the segmentation problem where features of the region to be segmented are embedded in region functional. All these contour or region-based methods used a level-set approach, which is accurate but time consuming.

Our strategy is different from those of previous edge sharpening methods. Our model is a combination of edge sharpening method with maximum cognate approach. This paper proposes a new morphological function, based on average pair of adjacent rows and adjacent columns that sharpens the boundary between features. It is derived using the concept of a morphological dilation and erosion and combined with estimation of the local neighborhood gradient, by adjacent pairs of rows and columns.

The proposed method of segmentation takes the advantage of implementing with a linear pipelined processor. This paper is organized as follows: In section 2, we briefly review the concept of linear pipelining. The methodology of extracting segmented image, based on cognate neighborhood approach, is presented in section 3. The experimental results and linear pipeline approach for segmentation is discussed in section 4. Concluding remarks are given in section 5.

II. Linear Pipelining

Pipelining offers an economical way to realize temporal parallelism in digital computers. The concept of pipeline processing in a computer is similar to assembly lines in an industrial plant. Assembly lines have been widely used in automated industrial plants in order to increase productivity. Their original form is a flow line (pipeline) of assembly stations where items are assembled continuously from separate parts along a moving conveyer belt. Ideally, all the assembly stations should have equal processing speed. Otherwise, the slowest station becomes the bottleneck of the entire pipe. This bottleneck problem plus the congestion caused by improper buffering may result in many idle stations waiting for new parts. The subdivision of the input tasks into a proper sequence of subtasks becomes a crucial factor in determining the performance of the pipeline [18]. Therefore to achieve pipelining, one must subdivide the input task into a sequence of subtasks, each of which can be executed by a specialized hardware stage that operates

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concurrently with other stages in the pipeline. Successive tasks are streamed into the pipe and get executed in an overlapped fashion at the subtask level. The subdivision of labor in assembly lines has contributed to the success of mass production in modern industry. By the same token, pipeline processing has led to the tremendous improvement of system throughput in the modern digital computer [18].

In an uniform-delay pipeline, all tasks have equal processing time in all station facilities. The stations in an ideal assembly line can operate synchronously with full resource utilization. However, in reality, the successive stations have unequal delays. The optimal participation of the assembly line depends on a number of factors, including the quality (efficiency and capability) of the working units, the desired processing speed, and the cost effectiveness of the entire assembly line.

The precedence relation of a set of subtasks $\{T_1, T_2, \ldots, T_k\}$ for a given task T implies that some task T_j cannot start until some earlier task $T_i (i<j)$ finishes. The interdependencies of all subtasks form the precedence graph. With a linear precedence relation, task T_j cannot start until all earlier subtasks $\{T_i$, for all $i<=j\}$ finish. A linear pipeline can process a succession of subtasks with a linear precedence graph.

The pipeline consists of a cascade of processing stages. The stages are pure combinational circuits performing arithmetic or logic operations over the data stream flowing through the pipe. The stages are separated by high-speed interface latches. The latches are fast registers for holding the intermediate results between the stages. Information that flows between adjacent stages is under the control of a common clock applied to all the latches simultaneously.

The present paper proposes a novel scheme of using pipeline of Processor Element (PE) to perform the segmentation approach. Pipeline processors are very fast. Each PE processes a part of operation before results begin to appear at its output and thus many PE stages may be cascaded. Many of the operations required during image processing do not require knowledge of the complete frame of an image, but only of a group of adjacent pixels or a neighborhood. If these operations are performed on a pipeline processor there is no need to store a complete image. The present segmentation algorithm is designated based on this approach. The novel nature of the proposed segmentation scheme lies in the fact that algorithm used to generate the segmented pixel which is divided into 4 passes.

III. Methodology

The segmentation of multiphase digital images is hindered by variation in brightness across individual features within the image. When feature brightness is uniform, the boundaries between features will be clear and separation of the phase is simply a matter of detecting the appropriate threshold for each phase present. However, if a gradual change in brightness from one phase to another occurs, segmentation is more difficult. To overcome this, edge sharpening is used in the present paper. When designing the edge-sharpening operator it was necessary to take into account the nature of the edges. The edge sharpening operator makes use of both the direction and magnitude of the gradient and is successful because of the shape of the edge surfaces. In this paper, gradients were defined in the horizontal and vertical directions using the means of grey levels of the local 5 x 5 neighborhood. Means were computed for each of ten pixels, of the adjacent rows and columns of 5 x 5 neighborhoods, where each row or column corresponds to 5 pixels elements. Like this on a 5 x 5 window by convolution one can obtain 4 pairs of adjacent rows and columns. The above scheme results 4 mean values for rows and columns of a 5 x 5 neighborhood. By further summation of adjacent rows and columns the present method obtains 3 mean values on row wise and column wise. A horizontal gradient exists if the mean across the middle falls between those above and those below. A vertical gradient exists if the mean value of the middle falls between those to the left and those to the right. If a pixel 'p' is on a gradient, it is assumed to be an edge. If pixel 'p' is on a gradient in both directions, the steeper of the two gradients is assumed to be an edge.

The entire process of segmentation using maximum cognate neighborhood approach is implemented by four passes.

Pass 1: Calculate adjacent Row and Column sums on a 5x5 neighborhood.

Step 1: Calculate adjacent Row and Col sums on a 5x5 neighborhood.

$$FRS_i = \sum_{i=1}^{4} RW_i + RW_{i+1}$$

$$FCS_i = \sum_{i=1}^{4} CW_i + CW_{i+1}$$

Where RWi represents sum of all i^{th} row elements, FRS_i is First Order row sum of two adjacent rows, and CWi represents sum of all i^{th} column elements, FCS_i is First Order Column sum of two adjacent columns.

Step 2: Calculate adjacent row and column sums from the previous step.

$$SRS_j = \sum_{j=1}^{3} FRS_j + FRS_{j+1}$$

$$SCS_j = \sum_{j=1}^{3} FCS_j + FCS_{j+1}$$

Where SRS_j is second order row sum of two adjacent FRS_i, and SCS_j is second order column sum of two adjacent FCS_i.

Pass2: Check Ascending or descending Row and Column sums of Pass1.

Pass3: Apply edge decrease followed by edge increase on entire image by convolution.

Pass 4: To achieve final segmentation count, the number of cognate grey level values that are above, below and equal to the central pixel of the 3x3 neighborhood. Based on this, replace the central pixel value by maximum cognate frequency value.

IV. RESULTS AND ANALYSIS

The proposed algorithm is applied on six Brodatz textures for evaluating its performance. The Brodatz textures are displayed in Fig. 1.

A good segmentation with region boundaries is obtained and shown in Fig. 2. This paper presents a computational model of texture segmentation. The results of these computational modeling experiments demonstrate both the need for and the power of combining approach of the above four-pass segmentation algorithm. The advantage of proposed segmentation method of 4 passes is, it can be applied easily on a linear pipelined processor. The linear pipeline with four stage design for the cognate neighborhood segmentation is shown in Fig 3. The input to the pipe line stage1 is the current 5X5 neighborhood of the image. The PE1 after calculating the adjacent row and column sums as explained in pass1 passes the output to pipelined PE2. While pipeline processor 2 is evaluating pass2, the PE1 reads and computes adjacent row and column sum of the next neighborhood. After four times slices all four pipelines PEs will be functioning and segmented pixel values will be resulted for every time slice. The space time diagram of Fig. 3 illustrates the overlapped operations of the proposed method with the suggested 4-stage linear pipeline. Once the pipe is filled up, it will output one result per clock period independent of the number of stages in the pipeline. Ideally a linear pipeline with k stages can process n tasks in $T_k = k + (n-1)$ clock periods, where k cycles are used to fill up the pipeline. The same number of tasks can be executed in a non-pipeline processor with an equivalent function $T_1 = n \times k$ clock periods. In Fig.3 N_1, N2-----N_n represents the convolving 5X5 neighborhood. An image of NXN will be having (N-4) × (N-4) convolving 5X5 windows. This results (N-4) × (N-4) segmented pixels. A pipelined processor with 4 stages can produce the segmented pixels in $4 + (n-5)^2$ clock periods. Where as a non-pipelined processor produces the segmented pixels in $(n-4)^2*4$ clock periods. The speed up of a 4-stage linear pipeline for cognate neighborhood segmentation over an equivalent non pipelined processor is given below.

$$((n-4)^2 * 4)/(4+(n-5)^2)$$

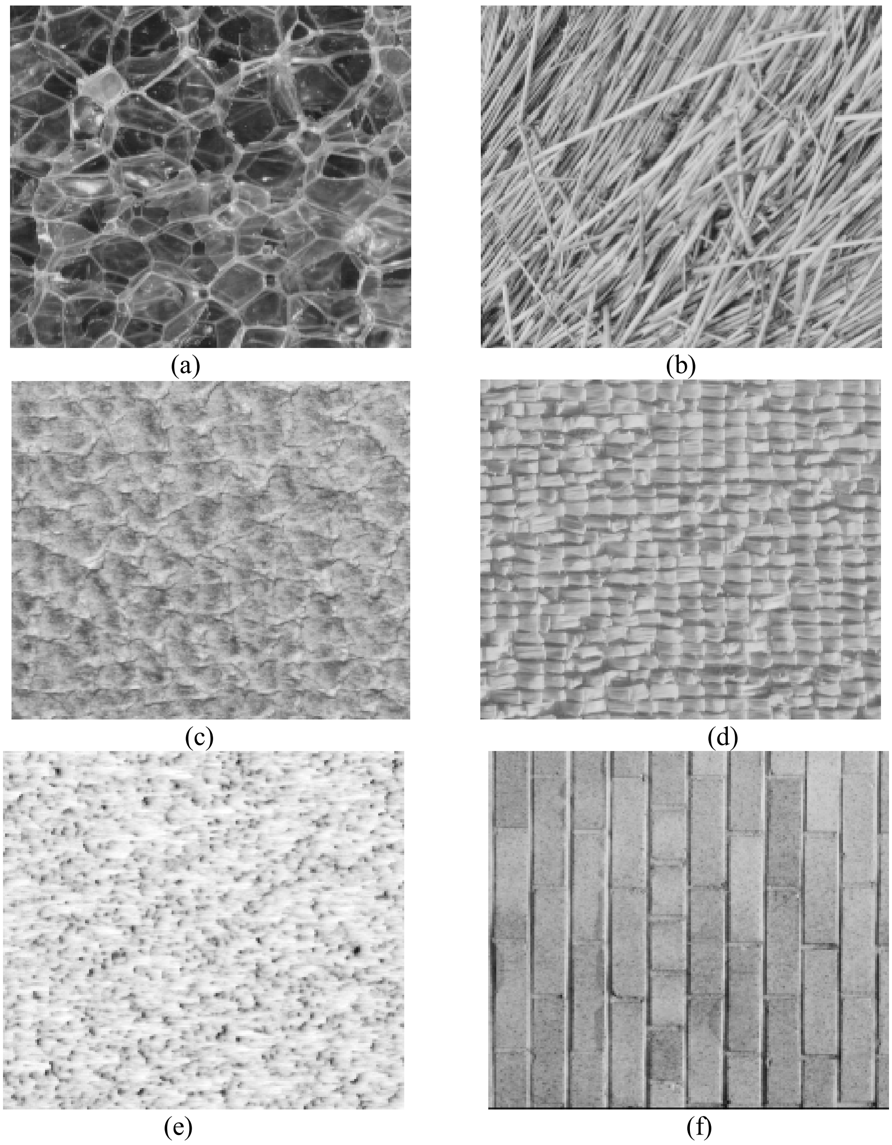


Fig.1. Original Images (a) Plastic Bubbles (b)Straw (c) Pig Skin (d) Raffia (e) Sand (f) Brick Wall

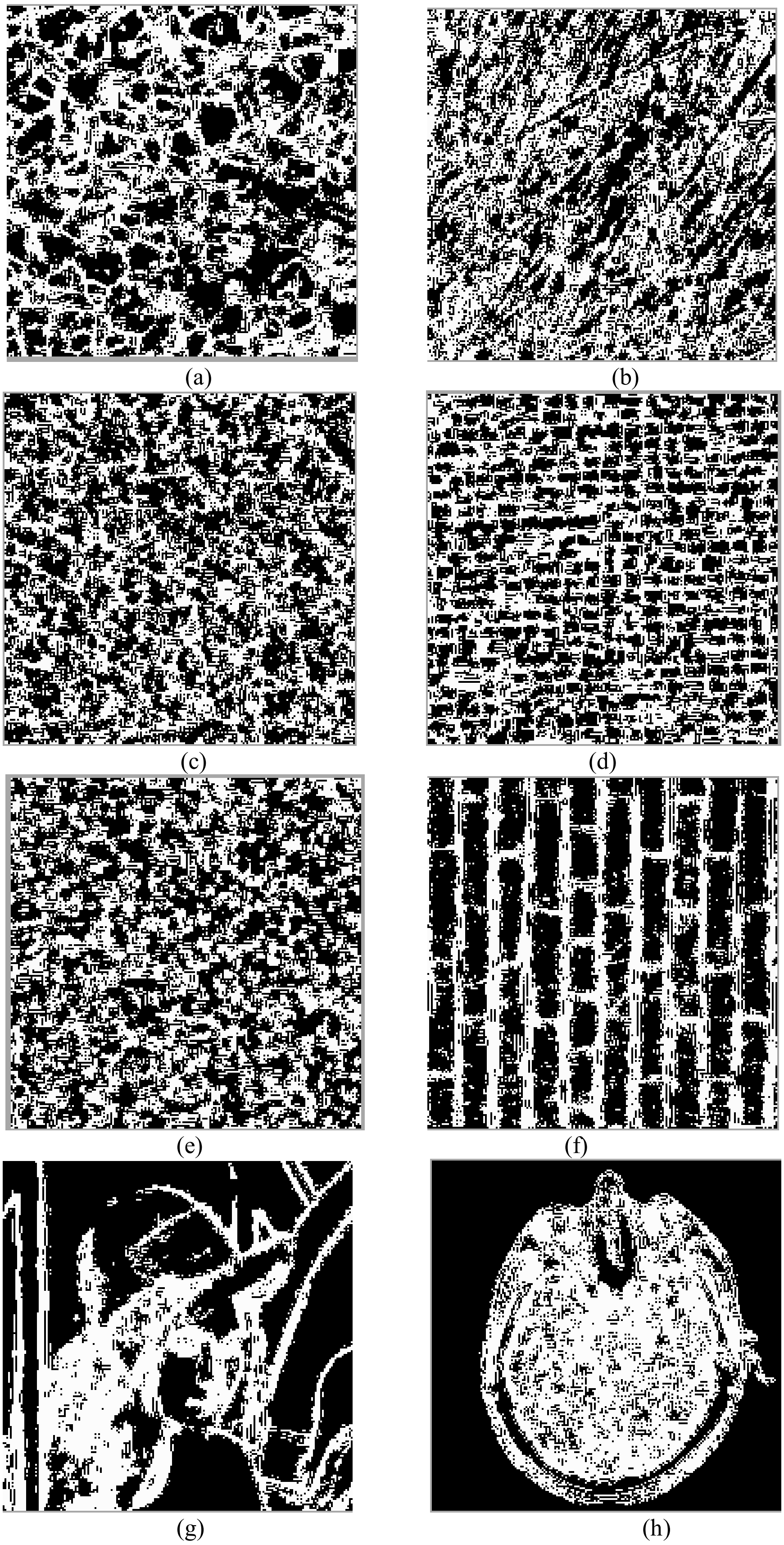
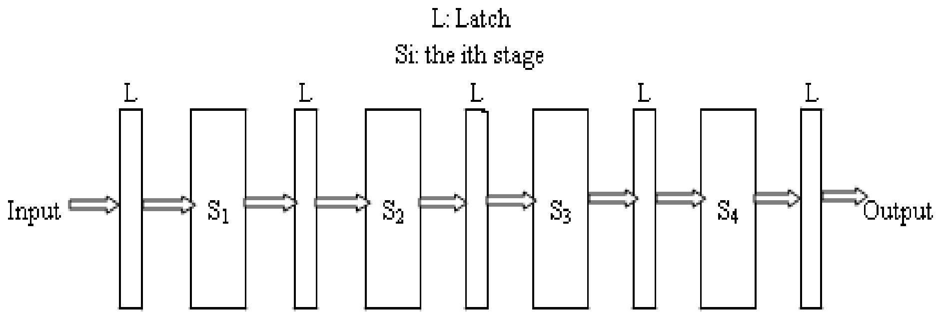


Fig.2. Segmented results of maximum cognate neighborhood approach. (a) Plastic Bubbles (b) Straw (c) Pig Skin (d) Raffia (e) Sand (f) Brick Wall (g) Leena (h) Brain MRI Image.

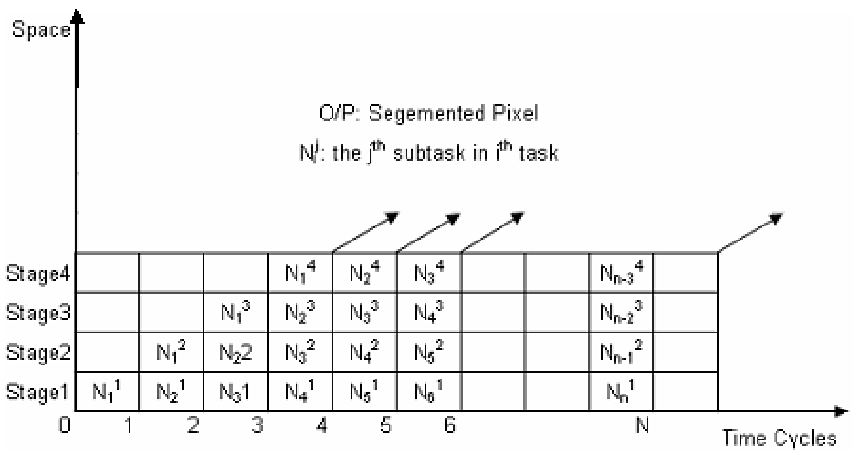
V. Conclusion

We have presented a novel segmentation technique to segment the image objects. It distinguishes itself from other approaches by dividing entire segmentation process into four overlapped passes. The segmented pixels on a 5X5 neighborhood will be obtained in the pass 4 with entirely a new approach called cognate neighborhood. The preprocessing steps edge increase and edge decrease makes the algorithm to work well on texture images containing dark and bright features. The proposed method of segmentation is applied not only on Brodatz textures but also on human face i.e. leena image and brain MRI image to have a comprehensive testing. The process of segmentation is divided into four passes to reduce the complexity and to achieve modularity. The following conclusions are drawn from this segmentation. An important advantage of this approach is that it works in much more general way and will not fail catastrophically due to the cognate neighborhood approach on edge sharpening of a 5X5 neighborhood. The cost of this neighborhood approach can be reduced by using pipelined processors that is while convolving the next 5X5 neighborhood, edge sharpening can be applied on the previous 5X5 convolution.

Experimental results on texture segmentation based on the combination of the suggested adjacent pairs of gradient on 5X5 mask, with primitive morphological operation of cognate neighborhood produces good boundaries on all Brodatz textures and other images considered. However some structural texture attributes generated from edge sharpening are sensitive to the edges but others such as the total quality of the pore and solid are not affected. The edge decrease decreases the edge levels where as the edge increase increases the edge levels. The edge sharpness is a useful initial step to avoid the halo effect around bright edges. The edge-sharpening operator, by means of edge decrease and edge increase, illustrates that it is useful in considering edges as two-dimensional surfaces. The combination of new approach “adjacent pairs of gradient on 5 x 5 masks” with primitive morphological operations illustrates that it can be considered a simple conventional neighborhood transformation. The developed cognate neighborhood approach operates without intervention of high knowledge and priori information. The process is automatic and results obtained are conclusive. A good segmentation is resulted on both the leena, and brain MRI image. This strengthens the validity of the algorithm. i.e. it can be applied on any type of image. When compared with other approaches, this method possesses the ability of implementation on a linear pipeline to reduce the overall computation time.



(a) A pipelined processor model for the proposed cognate neighborhood segmentation.



(b) Space-time diagram depicting the overlapped operations.

Fig. 3. Linear Pipeline Processor for overlapped Processing of Multiple Tasks of Cognate Neighborhood Segmentation

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