BRANCHES FILTERING APPROACH FOR MAX-TREE

Ketut E. Purnama[1], Michael. H. F. Wilkinson[2], Albert G. Veldhuizen, Peter. M. A. van Ooijen
Jaap Lubbers, Tri A. Sardjono and Gijbertus J. Verkerke[3]

[1,3]*Department of Biomedical Engineering, University Medical Center Groningen, University of Groningen*
P.O. Box 196, 9700 AD, Groningen, The Netherlands

[1]*Department of Electrical Engineering, ITS, Surabaya, Indonesia*

[2]*Institute for Mathematics and Computing Science, University of Groningen*
P.O. Box 800, 9700 AV, Groningen, The Netherlands

Keywords: Branches Filtering, Max-Tree.

Abstract: A new filtering approach called *branches filtering* is presented. The filtering approach is applied to the Max-Tree representation of an image. Instead of applying filtering criteria to all nodes of the tree, this approach only evaluate the leaf nodes. The expected objects can be found by collecting a number of parent nodes of the selected leaf nodes. The more parent nodes involve the wider the area of the expected objects. The maximum value of the number of parents (PL_{max}) can be determined by inspecting the output image before having unexpected image. Different images have found have different PL_{max} values. The branches filtering approach is suitable to extract objects in a noisy image as long as these objects can be recognised from its prominent information such as intensity, shape, or other scalar or vector values. Furthermore, the optimum result can be achieved if the areas which have the prominent information are present in the leaf nodes. The experiments to extract bacteria from noisy image, localizing bony parts in a speckled ultrasound image, and acquiring certain features from a natural image appeared to be feasible give the expected results. The application of the branches filtering approach to a 3D MRA image of human brain to extract the blood vessels gave also the expected image. The results show that the branches filtering can be used as an alternative filtering approach to the original filtering approach of Max-Tree.

1 INTRODUCTION

Separating objects from an image is a main issue in many applications of computer vision. Many methods have been proposed including the methods of mathematical morphology. A family of mathematical morphology called *connected operators* has been introduced and there is a great deal of development going on (Breen et al., 1996; Salembier et al., 1995) especially by the introduction of *Max-Tree* for image representation (Salembier et al., 1998). Connected operators, especially the ones that have anti-extensive property, are used to filter the expected objects based on one or more criteria. Objects extraction is not done to the original image. Instead, it is done to the Max-Tree, and the filtering criteria are applied to each node of the tree. The criteria can be shapes (Ouzounis et al., 2006; Urbach

et al., 2002; Wilkinson et al., 2001), vector attributes (Urbach et al., 2005) or other types of information.

In this paper, we proposed a new filtering approach called *branches filtering* which applies the filtering criteria only to the leaf nodes of Max-Tree. The expected objects can be found by collecting a number of parent nodes of the selected leaf nodes.

The next sections are organized as follows. Section 2 discusses the theory of connected operators for binary and grey-level image. The Max-Tree creation is discussed in Section 3. The description of the proposed branches filtering approach and its application to four different types of images are discussed in section 4. The discussion of our work is presented in section 5.

2 CONNECTED OPERATORS AND ANTI-EXTENSIVE CONNECTED OPERATORS

Connected operators in mathematical morphology are well known operators that preserve or remove connected components based on one or more filtering criteria. They never introduce new components. In detecting edges, for example, these operators can preserve the edge while removing noise or unwanted components. These operators can be applied to either binary or grey-level image. In the following paragraphs, the description of these operators is presented briefly. A more extensive description can be found elsewhere (Salembier et al., 1995; Serra et al., 1993).

A binary connected operator ψ is connected if and only if, for any binary image X, the associated partition of X is finer than the associated partition of $\psi(X)$. Let E be the universe of a set and partition $\{A_i\}$ is a set of connected components in E. A partition $\{A_i\}$ is said finer than partition $\{B_i\}$ if any pair of points of the same partition class A_i also belongs to a unique partition class B_i. The extension to grey-level image is applicable by associating a partition to a function. For each grey-level function f we obtain flat zones and the set of these flat zones is called partition of flat zones. Hence, the grey-level connected operator ψ is connected if and only if, for any grey-level image, the partition of flat zones of f is finer than partition of flat zones of $\psi(f)$.

In the rest of this paper, we inspect only connected operators that have anti-extensive property ($\forall x, \psi(X) \subseteq X$). The term connected component is used to refer to flat zone.

3 MAX-TREE FOR IMAGE REPRESENTATION

Max-Tree was first proposed by Salembier et al. (1998) as a tree data structure to represent a grey-level image. In the tree representation, the root node stores the pixels belonging to the background (pixels with the lowest grey-level). The nodes at the higher levels store pixels of each connected component found at higher grey-level. The leaf nodes represent the regional maxima of the image. The authors also proposed a filtering scheme consists of three steps. It is started by creating a Max-Tree representation of an image, then applying filtering criteria to all nodes of the tree, and followed by creating the output image from the filtered tree (image restitution).

The Max-Tree creation can be described as an iterative process. In the first iteration, the lowest grey-level is used as the threshold value h. Then, using this threshold value the pixels belong to the background are found, and a set of connected components is obtained from the pixels with grey-level higher than h. The background pixels are assigned to the root node, while the pixels of each connected component are assigned to a temporary node.

The next iterations are done as follows. The threshold value h is increased by one. For each temporary node, pixels with grey-level h are assigned to a new node. These nodes are then added to the tree. Again, a set of connected components is obtained from the pixels with grey-level higher than h. The pixels assigned by each connected component are assigned to a new temporary node. Figure 1 illustrates the Max-Tree creation process.

We use the following notations: C_h^k to refer to a kth node at level h, P_h^k to refer to a set of pixels that is assigned to C_h^k, and TC_h^k to refer to a kth temporary nodes at grey-level h.
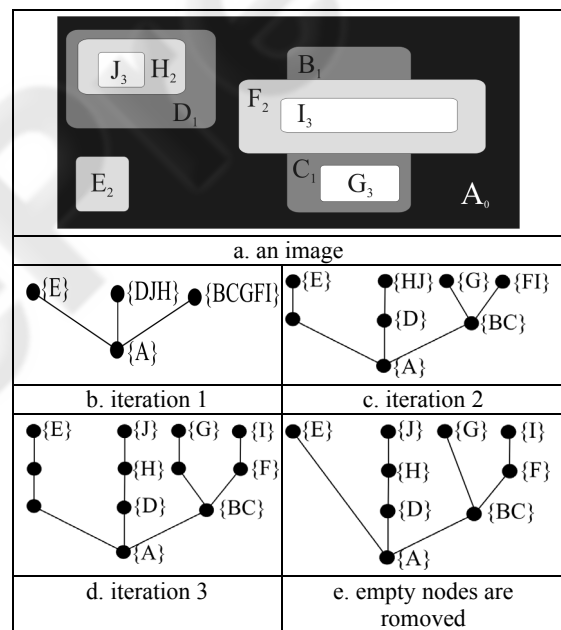

Figure 1: Max-Tree creation process. (a) input image, the first, the second, and the third iteration are illustrated in (b)-(d) respectively, and the empty nodes are excluded (e).

The image in Figure 1a is composed of ten connected components (A, B, C, D, E, F, G, H, I, and J) of four grey-level (0, 1, 2, and 3). The lowest grey-level of this image is 0. In the first iteration, we use this value as a threshold value (h). We find that

pixels in A have grey-level 0. The pixels of A are assigned to the root node C_0^1. We obtain three connected components (E, DJH, BCGFI) from the pixels with grey-level higher than h. The pixels of these connected components are assigned to temporary nodes: TC_1^1 ={E}, TC_1^2 ={DJH}, and TC_1^3 ={BCGFI}. The result of the first iteration is displayed in Figure 1b. In the second iteration, we increase *h* with one. Temporary node TC_1^1 has no pixel with grey-level *h*. Hence, we assign no pixel to a newly created node, and we still add this node to the tree. Temporary node TC_1^2 has one connected component with grey-level *h* (D) and one connected component with grey-level higher than *h* (JH). We assign the pixels of D to a new node and add this node to the tree. The pixels of JH are assigned to a temporary node. Shortly, for TC_1^3 a new node that is added to the tree refers to pixels in BC, while pixels in G and FI are assigned to two temporary nodes. The result of the second iteration is displayed in Figure 1c. The same process is applied to each temporary node in the third iteration, and we obtain the result in Figure 1d. Finally, the empty nodes are removed from the tree (Figure 1e).

In the filtering process, (Salembier et al., 1998) describes the filtering process using increasing and non-increasing criteria. Each node of Max-Tree is examined using a specific criterion. The result is whether the inspected node will be removed or preserved. Classical criteria were reported having increasing property. It includes: *opening by reconstruction* that preserves node C_h^k if the binary erosion of P_h^k is not the empty set; *grey-level area opening* that preserve C_h^k if the number of pixel of P_h^k is larger than a limit λ; $\lambda - max$ that preserve C_h^k if there is at least one non-empty set of its descendant nodes at level $h + \lambda$, and $\lambda - min$ that can be defined by the duality. For non-increasing criteria three rules are reported: "Direct", "Min" and "Max" decision. In the "Direct" decision C_h^k will be preserved if and only if $\kappa(C_h^k) \geq \lambda$. In this case, $\kappa(.)$ is a criterion. The P_h^k will be merged with the nearest ancestor. In "Min" decision, C_h^k will be preserved if $\kappa(C_h^k) \geq \lambda$ and all of its ancestors are also preserved. "Max" decision is dual

of the "Min" decision where C_h^k will be removed if $\kappa(C_h^k) < \lambda$ and all of its descendants are also removed.

4 BRANCHES FILTERING

In the original Max-Tree, the filtering criteria are applied to all nodes of the tree. The branches filtering approach acts differently; it applies the filtering criteria only to the leaf nodes. Based on the selected leaf nodes, a number of their parent nodes at the higher level is selected and preserved, while the other nodes are removed resulting in selected branches of the tree which represent the expected objects. By increasing the number of selected parents while inspecting the resulted image, the maximum value of the number of parents (PL_{max}) can be determined.

The idea of branches filtering approach was motivated by the fact that in some applications the expected objects are difficult to differentiate from unwanted neighbouring objects, or they are in the noisy image. This filtering approach is suitable if the expected objects can be recognized although by only a little information, and these information are present in the leaf nodes of Max-Tree.

Considering only the leaf nodes in the Max-Tree is comparable to extract the regional maxima of the image; (Vincent, 1993) use the grey scale reconstruction to extract all of the regional maxima (h-domes). However, branches filtering approach do not select all of the maxima, but just the maxima which fulfil the filtering criteria.

Figure 2 shows the application of this filtering approach on four different types of images. The images are grey-level images, and the values are between 0 and 255. We used grey-level as a criterion in the filtering process, and in the Max-Tree creation process this information was stored in each node. The first image is the inverted image of bacteria, and our objective is to extract the bacteria which has long rounded shape and typically chained with each other. Although it has unique shape, we do not use the shape as a criterion in the filtering process. Instead, we chose its grey-level. The second image is an axial view of the cross-section ultrasound image of human back. The objective is to extract the bony parts. Although bony structures will give strong reflection (high grey-level), the parts which have high grey-level are too small, and the neighbouring unwanted parts have grey-level

slightly the same. We need to enlarge the captured area without getting the unwanted parts. The third image is a 3D MRA image of human brain and the objective is to extract the blood vessels ignoring the cloudy parts around it. The last image is a natural image of a boy. The objective is to extract his image and the mask on his face.

The second, third and fourth rows display the influence of three different PL values to the resulted images. In our application the PL value was parameterized. The second row displays the results with PL is set to the minimum value (0); no parent node was included in the resulted image. The images in the fourth row resulted from the PL value equal to the PL_{max}. Different images have different PL_{max} value. The values around the half of PL_{max} value were used to obtain the images in the third row.
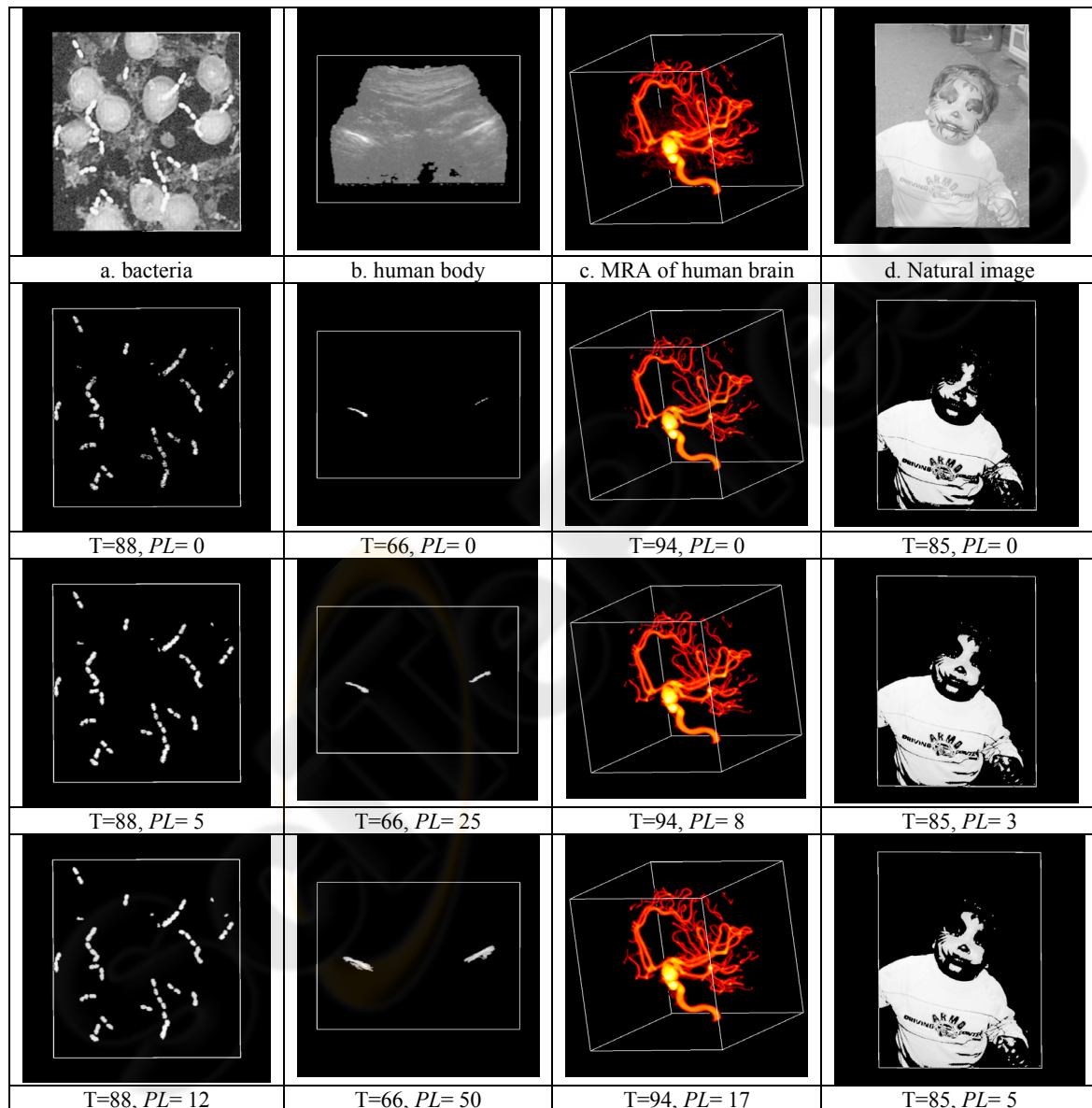

Figure 2: Branches filtering approach for different types of images (the first row) with a threshold value (T) and different parent level value (PL) in the second until fourth row. In the second row no parent node (PL=0) is selected; the parents until the PL_{max}th (fourth row) and around the half of PL_{max}th (third row) are selected.

5 DISCUSSION

We have shown a new filtering approach to the Max-Tree representation of an image called *branches filtering*. Instead of inspecting all nodes of the tree, the branches filtering applies the filtering criteria only to the leaf nodes. From the selected leaf nodes, the expected objects can be found by successively collecting a number of their parent nodes at the higher level. The maximum value of the number of parents (PL_{max}) can be determined by inspecting the resulted images before having unexpected result. Different images have different PL_{max} value. In case the grey-level is used as a criterion, the grey-levels stored in the leaf nodes can be sorted, then an automated process to determine the intensity threshold can be applied; we are working on it.

The results show that the *branches filtering* can be used as an alternative filtering approach to the original filtering approach of Max-Tree.

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