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Automatic attribute threshold selection for morphological connected attribute filters

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ABSTRACT

Attribute filters allow enhancement and extraction of features without distorting their borders, and never introduce new image features. In attribute filters, till date setting the attribute-threshold parameters has to be done manually. This research explores novel, simple, fast and automated methods of computing attribute threshold parameters based on image segmentation, thresholding and data clustering techniques in medical image enhancement. A performance analysis of the different methods is carried out using various 3D medical images of different modalities. Though several techniques perform well on these images, the choice of technique appears to depend on the imaging mode.

1. Introduction

Connected filters [1–3] have found application in medical image processing [4–10], image segmentation and reconstruction [11–15], object detection and recognition [16,17], document analysis [18], characters recognition [19] video processing [20], color processing [21,22] as well as remote sensing [23–27]. In most of these applications, the processing is directed towards classification or enhancement of regions of meaningful objects with respect to the application. In biomedical applications these objects might be tumors, kidney stones or aneurysms, whereas in remote sensing, the objects of interest may be roads, different types of buildings or vegetation, or damage caused by floods, landslides or earthquakes.

Early examples of connected operators include openings and closings by reconstruction [28,29] and area openings and closings [30]. These were generalized to the larger class of attribute openings, closings, thickenings, and thinnings [31], which together are called grey-scale attribute filters. For recent reviews see [1,32].

In attribute filters [31,20] filtering is based on properties of the desired image features. They work by computing some property, or *attribute* of image components, and preserving only those components which have the desired attribute values. An example of an attribute filter is shown in Fig. 1, in comparison to a classical morphological filter. As can be seen, in the connected case, image components can either be removed or remain intact but new ones do not emerge. This is a desirable property in many applications.

In the simplest form proposed in [31,20], attributes are compared against an *attribute-threshold*. Features with attributes above (or below) the threshold are preserved, the rest are removed. Choosing '*the best*' attribute threshold λ is done manually, which is subjective. Alternatively, a range of thresholds is used, e.g. to perform multi-scale analysis [33,25]. For filtering purposes, a single threshold is generally needed. Usually the threshold is obtained interactively [8] through trial and error. This is particularly tedious if the dynamic range of the attributes is large. Choosing '*the right*' λ is important because it determines what is retained or rejected, besides the filtering criteria. Indeed, all the problems in classical, grey-level threshold selection [34,35] occur in attribute threshold selection as well.

As there is a vast literature on threshold selection [36–43], it is only natural to explore the possibilities of adapting *grey-level* threshold selection techniques to *attribute* threshold selection. Therefore, we developed several automatic attribute threshold selection methods, by adapting conventional automatic grey-level thresholding techniques as well as data clustering techniques. Note that thresholding in the literature has been used as a pixel-level image processing procedure but never used for classification of regions or objects in an image, as it is in this work. Some

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Fig. 1. Left is the original image, middle is a structural opening with disk of radius = 20, which exhibits distorted borders and emergence of new features, Right is connected operator (area opening at threshold $\lambda = 100$), which shows no border distortion and regions are removed in their entirety.

preliminary results on blood-vessel enhancement were previously presented in [44]. In this paper we extend this research to include more threshold selection methods, and test these on 3D medical images of different modalities.

In principle, these techniques should work perfectly for all images but in this research the focus is 3D medical image enhancement and filtering. Two fundamental aspects of medical imaging make enhancement and filtering a difficult problem. The first aspect is the imaging process itself. The imaging process may fail to separate the anatomical feature of interest from its surroundings. The second fundamental aspect that makes filtering a difficult problem is that it needs to cope with the complexity and variability of the human anatomy. Manual selection of optimal processing parameters in medical imaging becomes complex, time-consuming and unfeasible when there are large numbers of images of varying quality, as often happens in medical images. Automatic choice of optimal parameter values is highly desirable.

The organization of the paper is as follows. Attribute filters are discussed briefly in Section 2. Section 3 discusses various threshold selection methods. Performance evaluation of the methods on various 3D medical images and document analysis are covered in Section 4. Performance is evaluated on noise suppression in document analysis and in 3D medical data sets. We show that several automatic techniques obtain threshold values close to those selected manually. In the case of document analysis, we show that for certain methods the resulting output image has an image quality similar to that of the best manual selection. Conclusions are given in Section 5.

2. Attribute filtering

In the following, a binary image X is considered a subset of some universal E. Foreground pixels are members of X, background pixels are in $E \backslash X$, where $\backslash$ denotes set difference. A grey-scale image is a function $f : E \rightarrow T$, with T being the totally ordered set of grey levels (usually $T \subseteq \mathbb{Z}$).

In the binary case, attribute filters [31] retain those connected components of an image which meet certain attribute criteria. After computing the connected components of X, i.e. the maximal connected subsets of X, some property or attribute of each component is computed. A threshold is usually applied to these attributes to determine which components are retained and which removed. Thus, the criterion Λ, usually has the form

$$\Lambda(C) = Attr(C) \geq \lambda \tag{1}$$

with C being the connected component, $Attr(C)$ some real-valued attribute of C and λ the attribute threshold.

Formally, attribute filters rely on connectivity openings γ_x, $x \in E$. In the binary case $\gamma_x(X)$ returns the foreground component to which x belongs if $x \in X$ and $\varnothing$ otherwise. After extracting the connected components using connectivity openings, a trivial filter ψ^Λ based on attribute criterion Λ is applied to each. These are defined as

$$\psi^\Lambda(C) = \begin{cases} C & \text{if } \Lambda(C) \text{ is true} \\ \varnothing & \text{otherwise.} \end{cases} \tag{2}$$

The attribute filter ψ_Λ based on criterion Λ is then defined as

$$\psi_\Lambda(X) = \bigcup_{x \in X} \psi^\Lambda(\gamma_x(X)) \tag{3}$$

In other words, $\psi_\Lambda(X)$ returns the union of all connected components which meet the criterion Λ.

Breen and Jones [31] build grey scale variants of binary filters by the standard method of threshold decomposition [45]. This means that for a grey scale image f, we compute these attributes for the connected components of threshold sets $X_h(f)$, defined as

$$X_h(f) = \{x \in E \,|\, f(x) \geq h\}. \tag{4}$$

In principle, we can apply the binary filter to each threshold set and stack the results. A more efficient approach uses the Max-Tree [20] data structure. The nodes $C_h{}^k$, with k being the node index and h the gray level of the Max-Tree represent connected components for all threshold levels in a data set. These components are referred to as *peak components* and are denoted as P_h^k. The root node represents the set of pixels belonging to the background, and each node has a pointer to its parent. An example of a Max-Tree is given in Fig. 2. Each node contains a reference to its parent, its original and filtered grey level and its attribute value or values in the case of vector-attribute filtering [46].

2.1. Attribute filter design

When designing an attribute filter, there are three points to consider in the binary case, and four in the grey-scale case. The first is which attribute to choose. Much work has been done developing attributes and algorithms to compute them efficiently [31,20,33,8,9,47]. In most cases a single attribute is computed for each component, but extensions to vector-attribute filters have been made [46,48].

The second point to consider is the which connectivity to use. This determines what constitutes a connected component, and therefore at what aggregation level in the image we are applying our attribute computation. Though in most cases we use 4 or 8 connectivity in 2D and 6 and 26 in 3D, the morphological connectivity theory developed in [49,50], and in particular for attribute filters in [51] allows more advanced choices of what constitutes a connected object.

The third consideration is that of the attribute criterion. In our case we will consider only the form in (1) (or its negation). This means that we are only left with the choice of the attribute threshold λ.