Biomedical Image Processing with Morphology and Segmentation Methods for Medical Image Analysis

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***Abstract*—Modern three-dimensional (3-D) medical imaging offers the potential and promise for major advances in science and medicine as higher fidelity images are produced. It has developed into one of the most important fields within scientific imaging due to the rapid and continuing progress in computerized medical image visualization and advances in analysis methods and computer-aided diagnosis[1],and is now, for example, a vital part of the early detection, diagnosis, and treatment of cancer. The challenge is to effectively process and analyze the images in order to effectively extract, quantify, and interpret this information to gain understanding and insight into the structure and function of the organs being imaged. The general goal is to understand the information and put it to practical use. A multitude of diagnostic medical imaging systems are used to probe the human body. They comprise both microscopic (viz. cellular level) and macroscopic (viz.organ and systems level) modalities. Interpretation of the resulting images requires sophisticated image processing methods that enhance visual interpretation and image analysis methods that provide automated or semi-automated tissue detection, measurement, and characterization [2–The objective of segmentation is to provide reliable, fast, and effective organ delineation. While traditionally, particularly in computer vision, segmentation is seen as an early vision tool used for subsequent recognition, in medical imaging the opposite is often true. Recognition can be performed interactively by clinicians or automatically using robust techniques, while the objective of segmentation is to precisely delineate contours and surfaces. This can lead to effective techniques known as "intelligent scissors" in 2D and their equivalent in 3D.**

This work develops two new filtering structures based on mathematical morphology that overcome the limitations of morphological filters while retaining their emphasis on shape. The linear combinations of morphological filters eliminate the bias of the standard filters, while the value-and-criterion filters allow a variety of linear and nonlinear operations to be used in the geometric structure of morphology. One important value-and-criterion filter is the Mean of Least Variance (MLV) filter, which sharpens edges and provides noise smoothing equivalent to linear filtering. To help understand the behavior of the new filters, the deterministic and statistical properties of the filters are derived and compared to the properties of the standard morphological filters. In addition, new analysis techniques for nonlinear filters are introduced that describe the behavior of filters in the presence of rapidly fluctuating signals, impulsive noise, and corners. The corner response analysis is especially informative because it quantifies the degree to which a filter preserves corners of all angles. Examples of the new nonlinear filtering techniques are given for a variety of medical images, including thermo graphic, magnetic resonance, and ultrasound images. The results of the filter analyses are important in deciding which filter to use for a particular application. For thermograph, accurate gray level estimation is required, so linear combinations of morphological operators are appropriate. In magnetic resonance imaging (MRI), noise reduction and contrast enhancement are desired. The MLV filter performs these tasks well on MR images. The new filters perform as well or better than previously established techniques for biomedical image enhancement in these applications.

Keywords: -

Spatial Filter, Image Denoising, Median Filter, Midrange Filter, Pseudo median Filter, Random Walkers.

I. Introduction

THE major strength in the application of computers to medical imaging lies in the use of image processing techniques for quantitative analysis. Medical images are primarily visual in nature; however, visual analysis by human observers is usually associated with limitations caused by interobserver variations and errors due to fatigue, distractions, and limited experience. While the interpretation of an image by an expert draws from his/her experience and expertise, there is almost always a subjective element. Computer analysis, if performed with the appropriate care and logic, can potentially add objective strength to the interpretation of the expert. Thus,it becomes possible to improve the diagnostic accuracy and confidence of even an expert with many years of experience.Imaging science has expanded primarily along three distinct but related lines of investigation: segmentation, registration and visualization [6].

The approach required is primarily that of problem solving. However, the understanding of the problem can often require a significant amount of preparatory work.The applications chosen for this book are typical of those in medical imaging; they are meant to be exemplary, not exclusive. Indeed, it is hoped that many of the solutions presented will be transferable to other problems. Each application begins with a statement of the problem, and includes illustrations with real-life images. Image processing techniques are presented, starting with relatively simple genericmethods, followed bymore sophisticated approaches directed at that specific problem.The benefits and challenges in the transition from research to clinical solution are also addressed.Biomedical imaging is primarily an applied science, where the principles of imaging science are applied to diagnose and treat disease, and to gain basic insights into the processes of life.The development of such capabilities in the research.laboratory is a time-honored tradition. The challenge is to make new techniques available outside the specific laboratory that developed them, so that others can use and adapt them to different applications. The ideas, skills and talents of specific developers can then be shared with a wider community and this will hopefully facilitate the transition of successful research technique into routine clinical use.Nonlinear methods in signal and image processing have become increasingly popular over the past thirty years.There are two general families of nonlinear filters: the homomorphic and polynomial filters, and the order statistic and morphological filters [1]. Homomorphic filters were developed during the 1970's and obey a generalization of the superposition principle [2]. The polynomial filters are based on traditional nonlinear system theory and use Volterra series. Analysis and design of homomorphic and polynomial filters resemble traditional methods used for linear systems and filters in many ways.The order statistic and morphological filters, on the other hand, cannot be analyzed efficiently using generalizations of linear techniques.The median filter is an example of an order statistic filter, and is probably the oldest [3, 4] and most widely used order statistic filter. Morphological filters are based on a form of set algebra known as mathematical morphology. Most morphological filters use extreme order statistics (minimum and maximum values) within a filter window, so they are closely related to order statistic filters [5, 6].While homomorphic and polynomial filters are designed and analyzed by the techniques used to define them, order statistic filters are often chosen by more heuristic methods. As a result, the behavior of the median filter and other related filters was poorly understood for many years. In the early 1980's, important results on the statistical behavior of the median filter were presented [7], and a new technique was developed that defined the class of signals invariant to median filtering, the root signals [8, 9]. Morphological filters are derived from a more rigorous mathematical background [10-12], which provides an excellent basis for design but few tools for analysis. Statistical and deterministic analyses for the basic morphological filters were not published until 1987 [5, 6, 13].The understanding of the filters' behavior achieved by these analyses is not complete, however, so further study may help determine when morphological filters are best applied.

II. Identification Of The Problems

1. Morphological filters are derived from a more rigorous mathematical background [10-12], which provides an excellent basis for design but few tools for analysis. Statistical and deterministic analyses for the basic morphological filters were not published until 1987.
2. The understanding of the filters' behavior achieved by these analyses is not complete, however, so further study may help determine when morphological filters are best applied.
3. The order statistic and morphological filters, on the other hand, cannot be analyzed efficiently using generalizations of linear techniques

III. Median Filter Roots Signals

The median filter is an order statistic (stack) filter that replaces the center value in the filter window with the median of the values in the window. If the values in the window are updated as the filter acts on the signal, it is called a recursive median filter. Non-recursive median filtering, which is far more common than recursive median filtering, always acts on the original values in the signal. For a signal $f(\mathbf{x})$ and a filter window W, the non-recursive median filter is denoted as shown in equation below:

1. Repeated application of the median filter is denoted by a superscript; for example, med3(f; W) denotes the result of three iterations of the non-recursive median filter with window W over the signal f. The root signal set of the 1-D median filter for finite-length signals consists only of signals that are everywhere locally monotonic of length $n + 2$, where W is $2n+1$ points long W =□2n(+1)□□[8, 9]. This means that any section of a finite-length median root signal of at least $n + 2$ points is monotonic (nonincreasing or nondecreasing). This result assumes the signal is padded appropriately with constant regions to obtain the filter output near the ends, as described previously. Gallagher and Wise [9] stated the same result slightly differently: a finite-length median root signal consists only of constant neighborhoods and edges. A constant neighborhood is an area of constant value of at least length $n + 1$ (just over half the length of W) and an edge is a monotonic region of any length between two constant neighborhoods.This root signal set indicates that the median filter preserves slowly varying regions and sharp edges, but alters impulses and rapid oscillations. For infinite-length signals, Tyan [8] showed that another type of root signal exists for the non-recursive median filter. These root signals, the ―fastfluctuating‖ roots, consist solely of rapid oscillations between two values. Nowhere in these signals is there even one monotonic region of length $n + 1$. For example, the infinite-length signal ..., 1, 0, 1, 0, 1, 0, 1, 0, ... is a root of the nonrecursive median filter with a window width of $4k+1$, where k is any positive integer. Although this type of signal is seldom encountered in practical applications, sections of a finite-length signal that fluctuate quickly (even if they are not bi-valued) are often passed by the median filter without much smoothing. An example

of this situation is shown in Figure 1. The original signal has an oscillation in it, and when filtered by a 5-wide median filter only the first and last two peaks in the oscillation are smoothed.

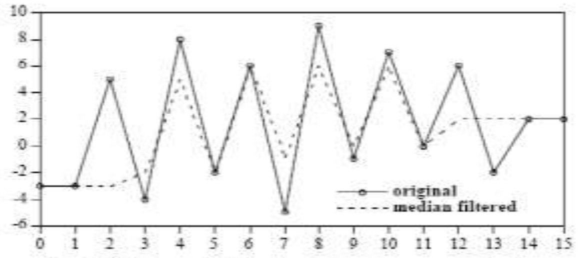

Figure 1. Oscillatory signal filtered by a 5-wide non-recursive median filter.

IV. Linear Combinations Of Morphological Operators

Since the complementary morphological operators (OC and CO; opening and closing; erosion and dilation) are equally and oppositely biased, an obvious way to try to remove the bias is by simply taking the average of the two operators. For symmetric input noise distributions, an evenly weighted average clearly should give an unbiased result; however, for asymmetric distributions an unequally weighted average of the two operators may work better for removing the bias.This chapter describes the various types of linear combinations of morphological operators and illustrates how they alleviate some of the bias problems of standard morphological filters. Theorems describing the root signal sets of these linear combinations are presented, and approximations for the statistical properties of the filters are also given and compared to the properties of the standard morphological filters.

a. *Midrange Filter*:-

The midrange filter is defined as the average of the maximum and the minimum values in a filter window, the midpoint of the range of values in the window. Since the erosion is a sliding minimum operation acting over the window N and dilation is a sliding maximum operation acting over the same window, another form of the midrange filter is the average of the two basic morphological operators, erosion and dilation. The midrange filter is a wellknown estimator in the order statistics literature; see, for example, [25-27]. The midrange filter is optimal in the mean square sense among all filters that are linear combinations of order statistics for removing uniformly distributed noise from a constant signal [26]. The midrange filter is also the maximum likelihood estimator for uniformly distributed noise [26].

***b.Pseudo median Filter* :-**

The pseudomedian filter was originally defined in 1985 by Pratt, Cooper, and Kabir [28]. They defined the filter in one dimension to be the average of the maximum of the minima of n+1 subwindows within an overall window and the minimum of the maxima of the same subwindows. Each subwindow is n+1 points long, and is within an overall window of length 2n+1. This structure corresponds to that of morphological opening and closing: the subwindows are the structuring elements N, and the overall window is W. Pratt recast the definition of the pseudomedian filter in his 1991 text [29] by forming the —maximin‖ and —minimax‖ functions, which he averages to find the pseudomedian. The maximin and minimax functions are equivalent to morphological opening and closing. The 1-D pseudomedian filter is therefore the average of the opening and closing, as noted previously by this author [30]. Pratt defined a two-dimensional pseudomedian filter in a manner that does not correspond to 2-D opening and closing; however, other work by the author [31, 32] generalized the pseudomedian filter to two dimensions in a manner corresponding to the definition of the pseudomedian as the average of opening and closing. The notation for pseudomedian filter is given in equation

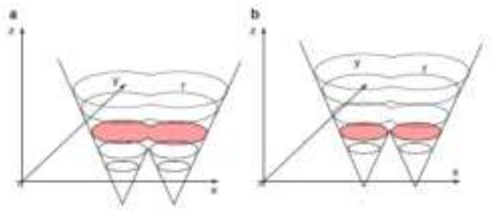

Fig2-(Embedding & evolve as a level set of a higher-dimention function)

***c. Image Analysis and Computer Vision*:-**

Segmentation can be studied from many angles. In computer vision, the segmentation task is often seen as a low-level operation, which consists of separating an arbitrary scene into reasonably alike components (such as regions that are consistent in terms of color, texture and so on). The task of grouping such component into semantic objects is considered a different task altogether. In contrast, in image analysis, segmentation is a high-level task that embeds high-level knowledge about the object. This methodological difference is due to the application field. In computer vision, the objective of segmentation (and grouping) is to recognize objects in an arbitrary scene, such as persons, walls, doors, sky, etc.

d. *Unifying Framework*

We propose to optimize the following general discrete energy:-

The p and q terms are integer exponents. In cases where the optimal x_ is not binary, we threshold it in the end as in (3.13). An analysis of the influence of p and q provides us with Table 1. In this table, we find some well-known algorithms, such as previously mentioned GR and RW, in addition to the Shortest Path Forests algorithm [20], that uses forests of shortest path leading to seeds as segmentation criteria. Most of the other cases are not interesting (Voronoi diagrams, for instance), but the case q = 1 or 2 and $p \rightarrow$ □ is novel and interesting: this is the Power Watershed algorithm [15]. **Table 1** Our generalized scheme for image segmentation includes several popular segmentation algorithms as special cases of the parameters p and q.The power watershed are previously unknown in the literature, but may be optimized efficiently with a MSF calculation Slide of a 3-D lung segmentation

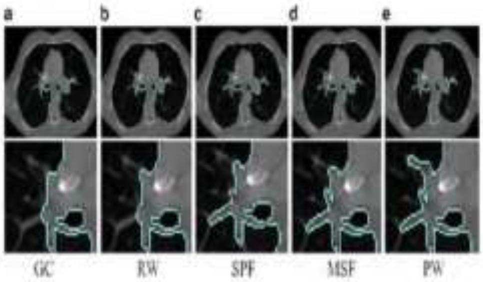

Figure 3: Slide of a 3-d lung segmentation

V. Results

Comparisons of four different filters at α□= 0 and at α= 45° are shown in Figures 8 and 9, respectively. The four filters are the square-shaped median, LOCO, and averaging filters and the plus-shaped median filter. Significant differences among the responses of these filters are easily observed. The corner ―passband‖ and ―stopband‖ information for these filters are collected in Table below. The ―perfect rejection‖ and ―perfect preservation‖ bands correspond to regions of □□ where r(□,α) = 0 and r(□,α) = 1 respectively.

Table 2. Comparison of filter corner responses

Filter (Shape)	Rotation	Perfect Rejection (r = 0) θ ≤	Stopband r<-10.7dB (r < .293) θ ≤	Transition Band Width	Passband r > -3dB (r > .707) θ ≥	Perfect Preservation (r = 1) θ ≥
Median (Square)	α = 0	27°	31°	17°	48°	180°
	α = 45°	19°	27°	22°	49°	180°
LOCO (Square)	α = 0	27°	31°	12°	43°	90°
	α = 45°	27°	32°	12°	44°	135°

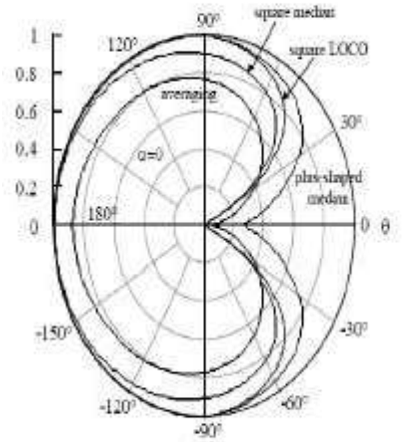

Figure 3: Comparison of fractional corner preservation square-shaped median LOCO and average filters and the plus median filter at corner rotation cum 0º

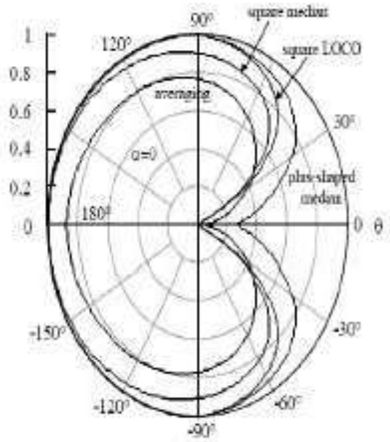

Figure 4: Comparison of fractional corner preservation square-shaped median LOCO and average filters and the plus median filter at corner rotation cum 45º

The values in Table above indicate that the square-shaped LOCO filter has the sharpest transition between corner removal and corner preservation for α□= 0, and that its response changes the least when α □changes from 0 to 45°. Thus, the LOCO filter is the closest of these four filters to an ―ideal‖ filter with a very small transition band and a corner response that changes little for different corner orientations. However, there are usually many considerations taken into account other than just the response at corners when selecting a two-dimensional filter. For example, the degree of noise reduction offered by the filters in Table varies, as does the type of noise they perform best against. Also, the corner response characteristics of opening, OC, CO, and the LOCO filter are all identical, despite obvious visual differences among the results of the filters in real image processing applications. Clearly, the corner response is not a complete description of the behavior of a filter. Although the corner response technique is a valuable analysis tool, it does not indicate how to design a filter with given corner response characteristics. The cutoff angles of filters vary with the angle of rotation α □and the shape of the filter, but usually the cutoff angle cannot be drastically changed for a given filter. Also,the fractional preservation r(□,α) only indicates the amount of area preserved, not any change in the shape of that area. Some filters, especially the median and morphological filters, achieve partial preservation of corners by changing the shape of the corners: the median filter rounds off sharp corners, while morphological operators tend to make corners look more like their structuring element. Thus a 45° corner filtered by open-closing with a square structuring element is 75% preserved [r(45°,0) = 0.75], but the result may look like a more obtuse angle because this operation tends to clip corners to make them as close to right angles as possible.

VI. CONCLUSION

This chapter introduced three new methods for analyzing the behavior of nonlinear filters. These analysis techniques demonstrate some important differences among the morphological, median, averaging, and MLV filters. Continuous time analysis yields the peak response of filters to periodic signals of different frequencies. This analysis highlights the differences between the morphological and non-morphological filters in the presence of rapidly fluctuating periodic signals or noise. The breakdown point gives a measure of the resistance of a filter to large outliers in its input. Using order statistics to limit the range of outputs of a filter allows custom filters with almost any breakdown point to be designed.The last technique developed in this chapter analyzes the behavior of twodimensional filters at corners. This method finds the fraction of corners of different angles and orientations preserved by a filter, and is important because it is one of very few techniques available to analyze the behavior of filters on twodimensional structures. The corner response of a filter gives an indication of whether the filter is more likely to preserve details and sharp features in an image or remove them. The analysis techniques introduced in this chapter provide a significant improvement in understanding the behavior of nonlinear filters, especially their response to high frequency periodic signals, impulse noise, and two-dimensional corners. In conclusion, we argue that seeded or interactive segmentation is useful in medical imaging. Compared with model-based segmentation, seeded segmentation is more robust in actual image analysis applications, as opposed to computer vision. The ability to separate seeds/markers, use contour information, and perform contour optimization are very useful, as these elements generally result in a higher likelihood of good results. From this point of view, we argue that segmentation is a process and not merely an operator.In general, the literature focuses on contour placement optimization at the expense of the other two components, with some rare exceptions. This is unfortunate but understandable with respect to seeds/markers, because they are highly application dependent. The choice of methods for obtaining contour information is also limited, and this is probably a good area for future research. One conclusion of this study is that contour placement optimization methods are important. More recent methods focus on optimization robustness, which is important. For someone not yet experienced in medical segmentation, simpler, more robust methods should be preferred over complex ones. Among those, power-watershed is a good candidate because of its combination of speed, relative robustness, ability to cope with multiple labels, absence of bias and availability (the code is easily available online). The random walker is also a very good solution, but is not generally and freely available. We have not surveyed or compared methods that encompass shape constraints.We recognize that this is important in some medical segmentation methods, but this would require another study altogether.

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