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METHODOLOGICAL REVIEW

Wavelets and Imaging Informatics: A Review of the Literature

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Modern medicine is a field that has been revolutionized by the emergence of computer and imaging technology. It is increasingly difficult, however, to manage the ever-growing enormous amount of medical imaging information available in digital formats. Numerous techniques have been developed to make the imaging information more easily accessible and to perform analysis automatically. Among these techniques, wavelet transforms have proven prominently useful not only for biomedical imaging but also for signal and image processing in general. Wavelet transforms decompose a signal into frequency bands, the width of which are determined by a dyadic scheme. This particular way of dividing frequency bands matches the statistical properties of most images very well. During the past decade, there has been active research in applying wavelets to various aspects of imaging informatics, including compression, enhancements, analysis, classification, and retrieval. This review represents a survey of the most significant practical and theoretical advances in the field of wavelet-based imaging informatics.

1. INTRODUCTION

With the steady growth of computer power, rapidly declining cost of storage, and ever-increasing access to the Internet, digital acquisition of biomedical images has become increasingly popular in recent years. A digital image is preferable to analog formats because of its convenient sharing and distribution properties. This trend has motivated research in imaging informatics [45, 48], which was nearly ignored by traditional computer-based medical record systems because of the large amount of data required to represent images and the difficulty of automatically analyzing images.

In addition to traditional X-rays and mammography, newer image modalities such as magnetic resonance imaging (MRI) and computed tomography (CT) can produce up to several hundred slices per patient scan. Each year, a typical hospital can produce several terabytes of digital and digitized medical images. Currently, storage is less of an issue since huge storage capacities are available at low cost. However, effective usage of large-scale biomedical image databases remains as a challenge for imaging informaticians.

Wavelets, studied in mathematics, quantum physics, statistics, and signal processing, are basis functions that represent signals in different frequency bands, each with a resolution matching its scale [7]. They have been successfully applied to image compression, enhancements, analysis, classification, and retrieval.

The outline of this paper is as follows. In Section 2, the

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concepts and definitions of wavelet transforms are introduced. In Section 3, previous research in the area of wavelet applications is summarized. Finally, conclusions are drawn and future directions are suggested in Section 4.

2. WAVELET TRANSFORMS

When constructing basis functions of a transform, the prime consideration is the localization, i.e., the characterization of local properties, of the basis functions in time and frequency. The signals we are concerned with are 2-D color or gray-scale images, for which the time domain is the spatial location of a pixel, and the frequency domain is the intensity or color variation around a pixel. An effective transform reflects intensity or color variations compactly in a small portion of transformation coefficients. With reduced components critical for representing an image, an image can be stored more efficiently and analyzed more easily. In this section, we compare a few representative transforms and their properties. Due to limit of space, we discuss the general concepts of wavelets here. Theories related to the development of wavelets can be found in several [14, 16, 18, 19].

Fourier Transform

Fourier transforms [9, 21] are not strange to image informaticians. In 1807, mathematician Joseph Fourier declared that any 2π-periodic function $f(x)$ is the sum of its Fourier series. That is,

$$f(x) = a_0 + \sum_{k=1}^{\infty} (a_k \cos kx + b_k \sin kx)\,, \tag{1}$$

where coefficients a_0, a_k, and b_k ($k = 1,2,3, \ldots$) are computed by the following equations:

$$a_0 = \frac{1}{2\pi}\int_0^{2\pi} f(x)\, dx \tag{2}$$

$$a_k = \frac{1}{\pi}\int_0^{2\pi} f(x) \cos kx dx \tag{3}$$

$$b_k = \frac{1}{\pi}\int_0^{2\pi} f(x) \sin kx dx\,. \tag{4}$$

The sequence

$$\frac{1}{\sqrt{2\pi}}, \frac{1}{\sqrt{\pi}}\cos x, \frac{1}{\sqrt{\pi}}\sin x, \frac{1}{\sqrt{\pi}}\cos 2x, \frac{1}{\sqrt{\pi}}\sin 2x, \ldots \tag{5}$$

is an orthonormal basis for the space of functions decomposable to the Fourier series on the interval $[0, 2\pi]$.

For discrete time signals, $f[n]$ can be expressed by a summation of discrete Fourier basis as

$$F[k] = \sum_{n=0}^{N-1} f[n] e^{-j2\pi nk/N} \tag{6}$$

$$f[n] = \frac{1}{N}\sum_{k=0}^{N-1} F[k] e^{j2\pi nk/N}, \tag{7}$$

where $F[k]$, referred to as the Fourier coefficients of $f[n]$, are determined by Eq. (6). The mapping from $f[n]$ to $F[k]$ is called the Discrete Fourier Transform (DFT). An alternative to the DFT is the Discrete Cosine Transform (DCT), which is often preferred because coefficients are guaranteed to be real numbers.

The Discrete Fourier Transform is widely used in signal and image processing, and has proven effective for numerous problems because of its frequency domain localization capability. It is ideal for analyzing periodic signals because the Fourier expansions are periodic. However, it lacks spatial localization due to the infinitely extending basis functions. Spline-based methods are efficient for analyzing the spatial localization of signals containing only low frequencies.

Many image applications share an important goal with image compression, i.e., to reduce the number of bits needed to represent the content of the original image. We now study the advantages and disadvantages of using the DCT transform for image compression.

The DCT is used in the JPEG (Joint Photographic Experts Group) compression encoding and decoding (codec) standard. To improve spatial localization, JPEG divides images into 8×8 nonoverlapping pixel blocks and applies the DCT to each block. The system quantizes each of the 64 frequency components uniformly using a quantization step specified by a table designed according to the human visual system (HVS)'s sensitivity to different frequencies. A smaller quantization step, or equivalently higher quantization accuracy, is used to quantize a frequency component to which the HVS is more sensitive. Entropy encoding using Huffman codes is applied to further reduce bits needed for representing an image.

Although spatial domain localization is improved by the windowed DCT, processing the 8×8 nonoverlapping blocks separately results in boundary artifacts at block borders, as shown in Fig. 1. Compression methods based on another set of orthogonal systems, the wavelets, typically generate much less visible artifacts at the same compression ratio.

Haar Wavelet

Orthonormal wavelet bases are an evolution of the Haar bases [39]. In 1909, Haar described orthonormal bases (in an appendix to his thesis), defined on [0, 1], namely $h_0(x)$, $h_1(x), \ldots, h_n(x), \ldots$, other than the Fourier bases, such that for any continuous function $f(x)$ on [0, 1], the series

$$\sum_{j=1}^{\infty} \langle f, h_j \rangle \, h_j(x) \tag{8}$$

converges to $f(x)$ uniformly on [0, 1]. Here, $\langle u, v \rangle$ denotes the inner product of u and v

$$\langle u, v \rangle = \int_0^1 u(x)\, \overline{v(x)}\, dx\,, \tag{9}$$

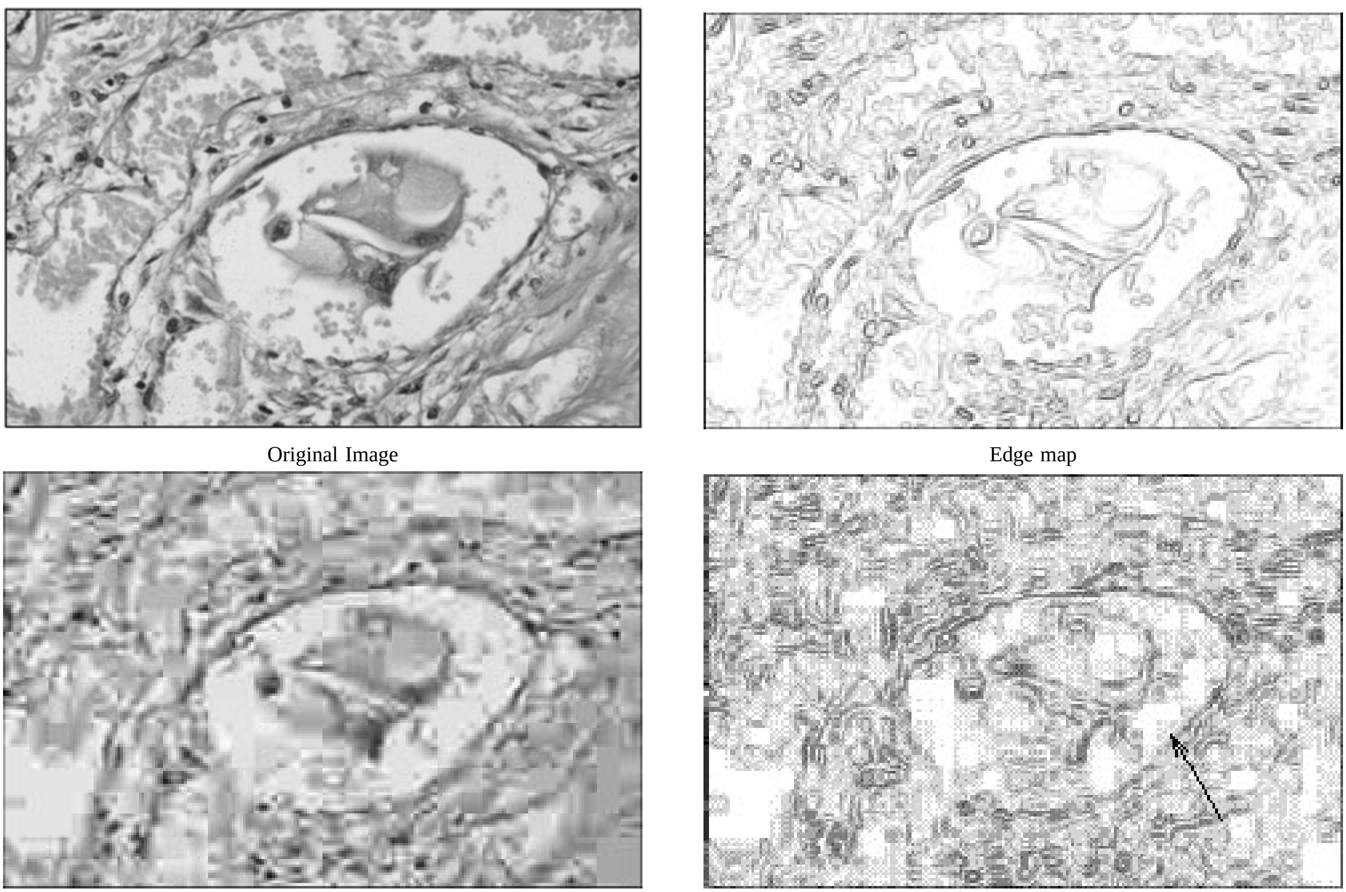
where $\bar{v}$ is the complex conjugate of v, which equals v if the function is real-valued.

One version of Haar's construction [7, 8, 39] is as

$$h(x) = \begin{cases} 1, & x \in [0, 0.5) \\ -1, & x \in [0.5, 1) \\ 0, & \textit{elsewhere} \end{cases} \tag{10}$$

$$h_n(x) = 2^{j/2} h(2^j x - k)\,, \tag{11}$$

where $n = 2^j + k$, $k \in [0, 2^j)$, $x \in [k2^{-j}, (k+1)2^{-j})$.



Original Image — Edge map

35:1 compressed JPEG — Edge map

FIG. 1. The Fourier transforms create visible boundary artifacts.

There are limitations in using Haar's construction. Because Haar's base functions are discontinuous step functions, they are not suitable for analyzing smooth functions with continuous derivatives. Since images often contain smooth regions, the Haar wavelet transform does not provide satisfactory results in many applications.

Daubechies' Wavelets

Many other types of wavelets have been developed to improve the Haar wavelet transform. One representing type of basis for wavelets is that of Daubechies. For each integer r, the orthonormal basis [13, 27, 36, 37] for $L^2(\mathbb{R})$ is defined as

$$\phi_{r,j,k}(x) = 2^{j/2}\,\phi_r(2^j x - k),\; j, k \in \mathbb{Z}\,, \tag{12}$$

where the function $\phi_r(x)$ in $L^2(\mathbb{R})$ has the property that $\{\phi_r(x-k) | k \in \mathbb{Z}\}$ is an orthonormal sequence in $L^2(\mathbb{R})$. Here, j is the scaling index, k is the shifting index, and r is the filter index.

Then the *trend* f_j, at scale 2^{-j}, of a function $f \in L^2(\mathbb{R})$ is defined as

$$f_j(x) = \sum_k \langle f, \phi_{r,j,k}\rangle\, \phi_{r,j,k}(x)\,. \tag{13}$$

The *details* or *fluctuations* are defined by

$$d_j(x) = f_{j+1}(x) - f_j(x)\,. \tag{14}$$

To analyze these details at a given scale, we define an orthonormal basis $\psi_r(x)$ with properties similar to those of $\phi_r(x)$ described above. $\phi_r(x)$ and $\psi_r(x)$, called the *father wavelet* and the *mother wavelet*, respectively, are the wavelet prototype functions required by the wavelet analysis. Figure 2 shows several popular mother wavelets. Wavelets such as those defined in Eq. (12) are generated from the father or the mother wavelet by changing scale and translation in time (or space in image processing).

Daubechies' orthonormal basis has the following properties:

- ψ_r has the compact support interval $[0, 2r+1]$
- ψ_r has about $r/5$ continuous derivatives
- $\int_{-\infty}^{\infty} \psi_r(x)dx = \ldots = \int_{-\infty}^{\infty} x^r \psi_r(x)dx = 0.$

Daubechies' wavelets provide excellent results in image processing due to the above properties. A wavelet function with compact support can be easily implemented by finite length filters. Moreover, the compact support enables spatial domain localization. Because the wavelet basis functions have continuous derivatives, they decompose a continuous function more efficiently with edge artifacts avoided. Since the mother wavelets are used to characterize details in a signal, they should have a zero integral so that the trend information is stored in the coefficients obtained by the father wavelet. A Daubechies' wavelet representation of a function is a linear combination of the wavelet basis functions.

Daubechies' wavelet transforms are usually implemented numerically by quadratic mirror filters [3, 10, 39]. Multiresolution analysis of the trend and fluctuation of a function is

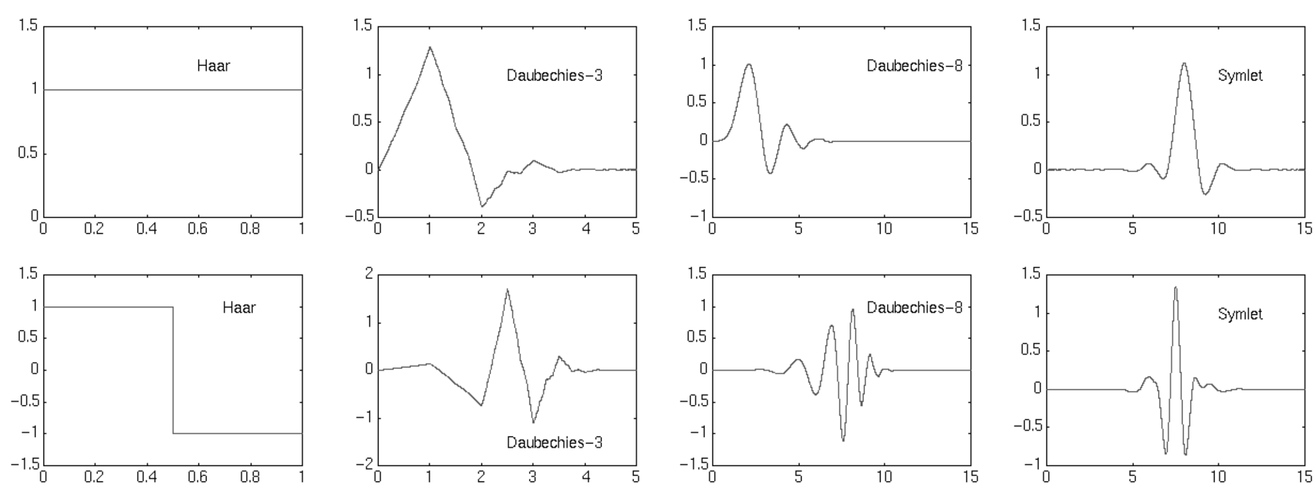


FIG. 2. Plots of some analyzing wavelets. First row: father wavelets $\phi(x)$. Second row: mother wavelets, $\psi(x)$.

implemented by convolving it with a low-pass filter and a high-pass filter that are versions of the same wavelet. The Haar wavelet transform is a special case of Daubechies' wavelet transform with $r = 2$, which is termed as Daubechies-2 wavelet transform.

The transform of signal $x(n)$, $n \in \mathbb{Z}$ by the Haar's wavelet is provided by

$$F_0\,(x(n)) = \frac{1}{\sqrt{2}}\,(x(n) + x(n+1)) \tag{15}$$

$$F_1\,(x(n)) = \frac{1}{\sqrt{2}}\,(x(n) - x(n+1))\,. \tag{16}$$

The corresponding low-pass filter is $\left\{\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\right\}$ and the high-pass filter is $\left\{\frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}}\right\}$.

In fact, averaging on adjacent samples is equivalent to using transform coefficients obtained by the low-pass filter of the Haar's wavelet. Daubechies' wavelets transforms with $r > 2$ are analogous to weighted averaging which better preserves the trend information in signals if we consider only the low-pass filter part. Various experiments and studies [46] have shown that in many cases Daubechies' wavelets with $r > 2$ result in better performance than the Haar's wavelet.

Figure 3 shows a comparison of the Haar wavelet, equivalent to averaging, and the Daubechies-8 wavelet. We notice that the signal with a sharp spike is better analyzed by Daubechies' wavelets because much less energy or trend is stored in the high-pass bands. Daubechies' wavelets are better suited for natural signals or images than the Haar wavelet. In many image applications, we want to represent as much energy in the image as possible in the low-pass band coefficients. When using the Haar wavelet, we lose more trend information if we ignore the high-pass bands.

In general, Daubechies' wavelets with long-length filters give better energy concentration than those with short-length filters. However, processing discrete images using long-length wavelet filters often causes border problems. Usually we need to determine the filter to be used base on applications.

3. APPLICATIONS OF WAVELETS IN IMAGING INFORMATICS

Wavelets have been successfully used in many signal processing applications such as electrocardiogram (ECG) [12, 25] and speech [26]. In this paper, we focus on their applications in imaging informatics.

There is a wealth of prior work in the field of imaging informatics using wavelets. Space limitations do not allow us to present a broad survey in detail. We constrain ourselves to highlighting some of the work that may be most representative.

Compression and Progressive Transmission

Because of the high compressibility of the biomedical images, data compression is desirable for efficient transmission and storage. For example, the success of a telemedicine

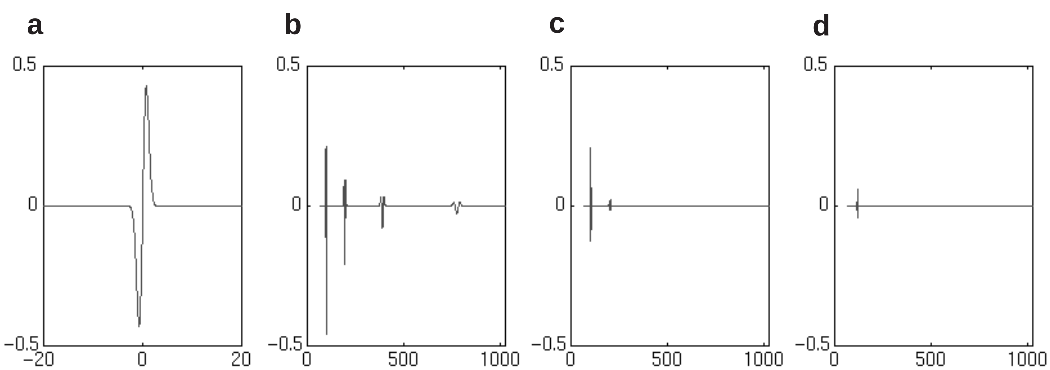


FIG. 3. Comparison of Haar's wavelet and Daubechies' wavelets on a 1-D signal. (a) Original signal (χe^{-x^2}) length 1024. (b) Coefficients in high-pass bands after a four-layer Haar transform. (c) Coefficients in high-pass bands after a four-layer Daubechies-3 transform. (d) Coefficients in high-pass bands after a four-layer Daubechies-8 transform.

system or a Picture Archive and Communications Systems (PACS) system relies critically on the speed images or video clips are transmitted. Usually the network bandwidth is limited and the amount of data stored in a biomedical image is enormous. Real statistical clinical-quality evaluations have shown that wavelet-based image compression algorithms can result in 10-fold efficiency without visible artifacts [1].

We now survey the family of wavelet-based progressive image compression algorithms. The progressive property is preferred because it allows users to recover images gradually from low to high quality. An image can be encoded losslessly, but the user can choose a bit rate sufficient for his or her particular needs by simply using part of the encoded bit stream.

Image compression is a major application area for wavelets. Because the original image can be represented by a linear combination of the wavelet basis functions, similar to Fourier analysis, compression can be performed on the wavelet coefficients.

The wavelet transform offers good time and frequency localization. Information stored in an image is decomposed into averages and differences of nearby pixels. For smooth areas, the difference elements are near zero. The wavelet approach is therefore a powerful tool for data compression, especially for functions with long-range slow variations and short-range sharp variations [49]. The time and frequency localization of the basis functions are adjusted by both scale index j and position index k. We may decompose the image even further by applying a wavelet transform several times recursively.

Figure 4 shows the multiscale structure in the wavelet transform of an image. An original MRI image of 256×256 pixels is decomposed into a three-level wavelet transform of 256×256 coefficients. Coefficients in a one-level wavelet transform are organized into four bands, emphasizing low-frequency trend information, vertical-directional fluctuations, horizontal-directional fluctuations, and diagonal-directional fluctuations, respectively. The low-frequency band of coefficients can be further decomposed to form higher-level wavelet transforms. The figure shows wavelet transforms after thresholding near zero. Most of the high-frequency coefficients are of near-zero values. Note that information about the shape, intensity, and surface texture is well preserved and organized in different scales for analysis.

Since wavelet transforms decompose images into several resolutions, the coefficients, in their own right, form a successive approximation of the original images. For this reason, wavelet transforms are naturally suited for progressive image compression algorithms. In 1992, De Vore *et al.* discovered an efficient image compression algorithm by preserving only the largest coefficients (which are scalar quantized) and their positions [15]. In the same year, Lewis and

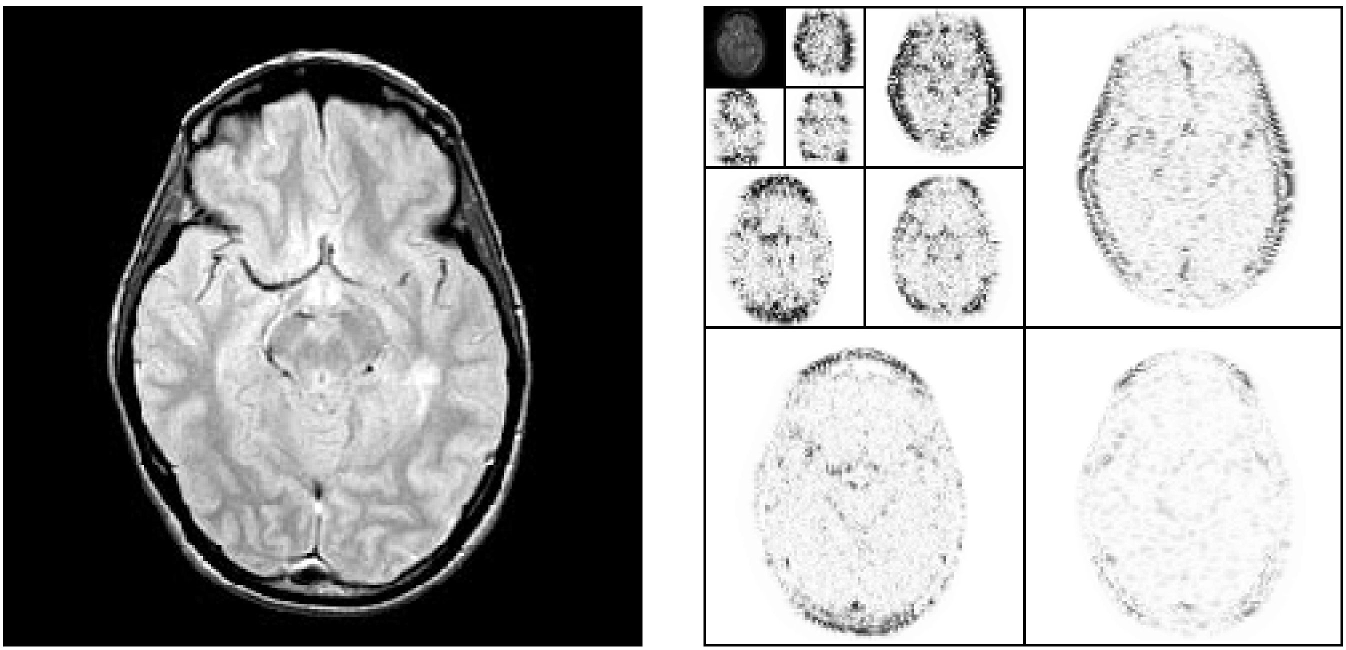


FIG. 4. A three-level wavelet transform of an MRI image slice using Daubechies' wavelet. Plotted dots indicate non-zero wavelet coefficients after thresholding.

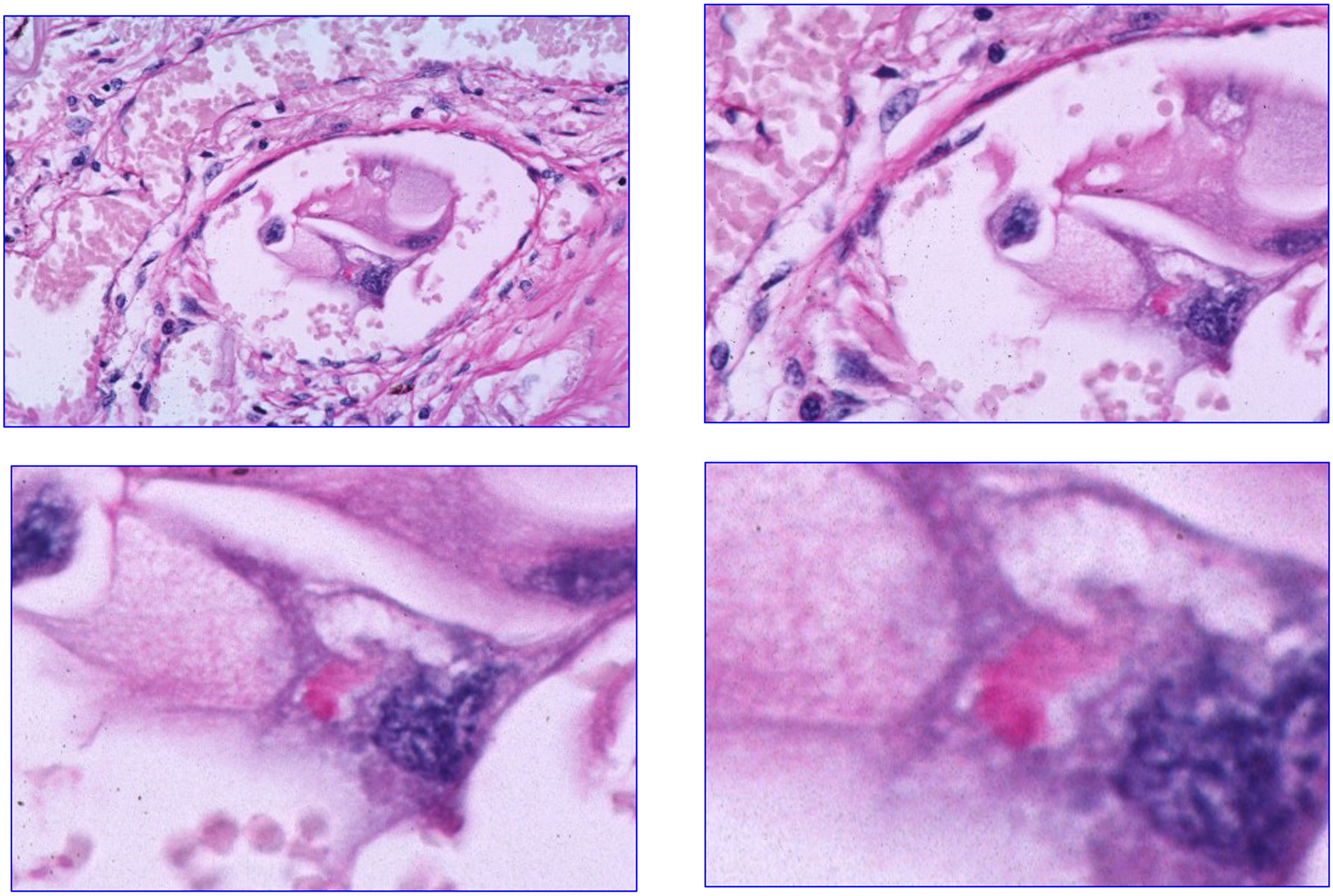


FIG. 5. Multiresolution progressive browsing of pathology slides of extremely high resolution. The HTML-based interface is shown. The magnification of the pathology images is shown on the query interface.

Knowles published their image compression work using 2-D wavelet transform [29] and a tree-structured predictive algorithm to exploit the similarity across frequency bands of the same orientation. There is also other work in the same period of time [2].

Many current progressive compression algorithms apply quantization on coefficients of wavelet transforms which became more widely used after Shapiro's [44] invention of the zero-tree structure, a method to group wavelet coefficients across different scales to take advantage of the hidden correlation among coefficients. A major breakthrough in performance was achieved. Much subsequent research has taken place based on the zero-tree idea, including a very significant improvement made by Said and Pearlman [43], referred to as the S & P algorithm. This algorithm was applied to a large database of mammograms by a group of researchers at Stanford University [1, 40] and was shown to be highly efficient even by real statistical clinical-quality evaluations.

An important advantage of the S & P algorithm and many other progressive compression algorithms is the low encoding and decoding complexity. No training is needed since trivial scalar quantization of the coefficients is applied in the compression process. However, by trading off complexity, the S & P algorithm was improved by tuning the zero-tree structure to specific data [20].

A progressive transmission algorithm with automatic security filtering features for on-line medical image distribution using Daubechies' wavelets has been developed by Wang, Li, and Wiederhold of Stanford University [52]. Figure 5 shows sample image query results with the HTML-based client user interface.

Other work in this area include the work by LoPresto *et al.* on image coding based on mixture modeling of wavelet coefficients and a fast estimation–quantization framework [33], the work by Villasenor *et al.* on wavelet filter evaluation for compression [50], and the work by Rogers and Cosman on fixed-length packetization of wavelet zero-tree [42].

A recent study by a group of radiologists in Germany [41] concluded that only wavelets provided accurate review of low-contrast details at a compression of 1:13, tested among a set of compression techniques including wavelets, JPEG, and fractal.

Enhancements

Image smoothing, denoising, and other enhancements are also significant applications of wavelets in imaging informatics. Radiology images are typically noisy and of low contrast because of the physical limitations of the acquiring devices. Efficient image enhancement is often desired by radiologists.

Image enhancement methods are also often used as preprocessors for image analysis, image classification, and image retrieval applications. For example, to extract meaningful features from a noisy medical image and index it in a medical image database, we must perform a series of image enhancement operations such as image denoising and image normalization to the original image.

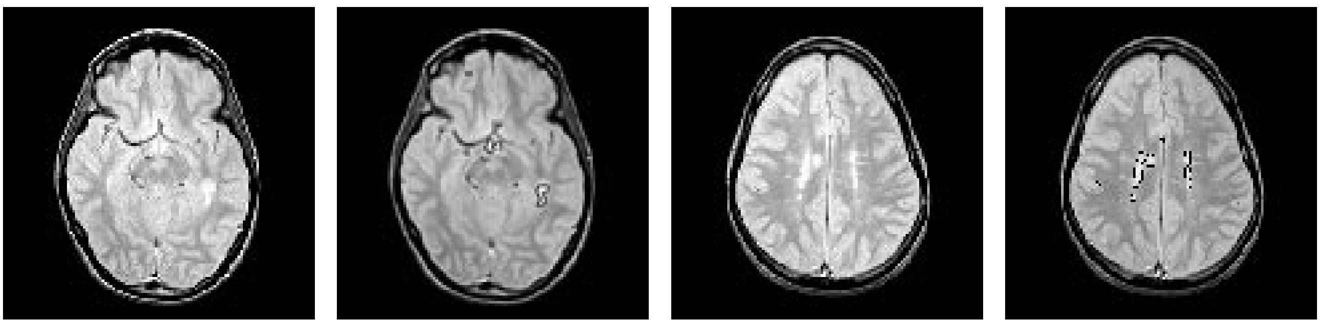
A successful image denoising algorithm should preserve the useful information in the image while removing machine-introduced noise. Wavelet is suitable for denoising because a noise signal usually has greatly different frequency properties from those of an image signal, which are reflected by wavelet transform coefficients.

Weaver *et al.* of the Dartmouth–Hitchcock Medical Center in New Hampshire are among the first to use wavelets in denoising of medical images [59]. Their method does not reduce the sharpness of edges. However, a major problem is the elimination of small structures that are similar in size to the noise to be removed.

Yu *et al.* of Stanford University developed a translation- and direction-invariant denoising algorithm for both 2-D and 3-D images using wavelets [62]. The denoising process is essentially a signal extraction process. Wavelet-based approach is quite different from traditional filtering approaches because of its nonlinear property. A typical wavelet-based denoising algorithm has the following steps: (1) perform a suitable wavelet transform of the noisy data; (2) perform a soft thresholding of the wavelet coefficients where the threshold depends on the noise variance; (3) coefficients obtained from step 2 are then padded with zeros to produce a matrix and the matrix is inverted to obtain the signal estimation. Examples have shown that this approach suppressed the noise effectively while maintaining features in the original signal.

Other recent work in wavelet-based image denoising includes the work by Stoschek and Hegerl on denoising of electron tomographic reconstructions [47], the work by Weaver on monotonic noise suppression used to improve the sensitivity of fMRI activation maps [60], and the work by Zong *et al.* on speckle reduction and contrast enhancement of echocardiograms [64].

Laine *et al.* have used wavelets for contrast enhancement and feature extraction of digital mammography [28]. Lu and Healy of Dartmouth College developed another contrast enhancement technique for medical images using a multiscale wavelet-based edge representation [34]. They used the edge detection and classification properties of wavelet-type representations. Experiments have been conducted on various imaging modalities. One particular diagnostic application is the tracking of heart wall thickness during the cardiac cycle [23].



T2-weighted MS lesions T2-weighted MS lesions

FIG. 6. Automatic classification of MRI images: No pre- or postprocessing.

Analysis and Classification

Image classification is a technique for classifying images or areas of images into several categories. In the medical domain, image classification can be categorized into global classification and local classification, based on the targeted tasks.

- Global classification: One example is to discern images with lesions (abnormal cases) and images without lesions (normal cases).
- Local classification or image segmentation: One example is to identify the regions, or set of pixels, representing certain objects (e.g., the lesions, the blood vessels). Figure 6 shows an example of a local classification process. In this example, the computer algorithm circled possible multiple sclerosis lesions after analyzing wavelet transforms of the multispectrum MRI images.

In many applications, global classification is achieved by local classification and statistical analysis.

Lucier *et al.* of Purdue University developed a wavelet-based segmentation algorithm for digital mammograms [35]. However, the less advanced Haar wavelet transform is used in the algorithm. Their study has shown that the artifacts in the compressed images were seen as totally artificial and were not misinterpreted by the radiologist as calcifications. The compressed images were also processed by a wavelet method to extract the calcifications. Despite several false-positive signals in highly compressed images, all true clusters were successfully segmented.

Similar successes have been achieved by Wei *et al.* of the University of Michigan [61], Zheng *et al.* of the Texas A&M University [63], Li *et al.* of the University of South Florida [32], and Mata Campos *et al.* of Spain [38].

Recently, Wang *et al.* of Stanford University developed a wavelet-based unsupervised multiresolution segmentation for images with low depth of field such as digital microscope images [55]. The algorithm is designed to separate a sharply focused object-of-interest from other foreground or background objects. The algorithm is fully automatic in that all parameters are image independent. This work represents context-dependent classification of individual blocks of the image.

Wavelets incorporated with multiresolution models have resulted in great performance in many image processing tasks. One example is the two-dimensional multiresolution hidden Markov model (2-D MHMM) developed by Li, Gray, and Olshen [30] for image classification and compression. In conventional block-based classification algorithms, an image is divided into blocks and the class of each block is determined independently according to features extracted from this block. To improve classification by incorporating context information efficiently, features at multiple resolutions are extracted using wavelet transforms in particular. Then the 2-D MHMM is proposed to characterize both interresolution and intraresolution statistical dependence among image blocks. Figure 7 illustrates the interresolution dependence in the 2-D MHMM. Other examples of multiresolution models using wavelets include the multiscale random field model developed by Bouman and Shapiro [4] and the hidden Markov model for wavelet coefficients developed by Crouse, Nowak, and Baraniuk [11].

Retrieval

Content-based image retrieval (CBIR) is a technique for retrieving relevant images from an image database on the basis of automatically derived image features. CBIR functions differently from text-based image retrieval. Features describing image content, such as color histogram, color layout, texture, shape, and object composition, are computed for both images in the database and query images. These features are then used to select the images that are most similar to the query. High-level semantic features such as the types of objects in the images and the purpose of the images are extremely difficult to extract. Derivation of semantically meaningful features remains a great challenge.

CBIR is critical in developing patient care digital libraries.

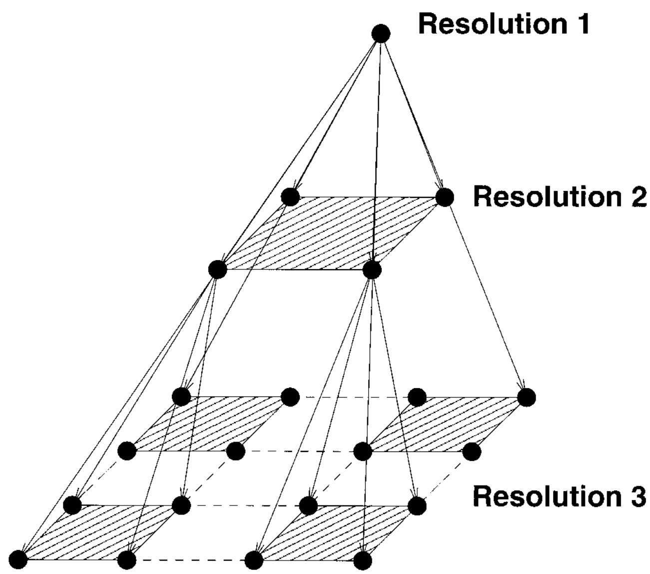


FIG. 7. The hierarchical statistical dependence across resolutions.

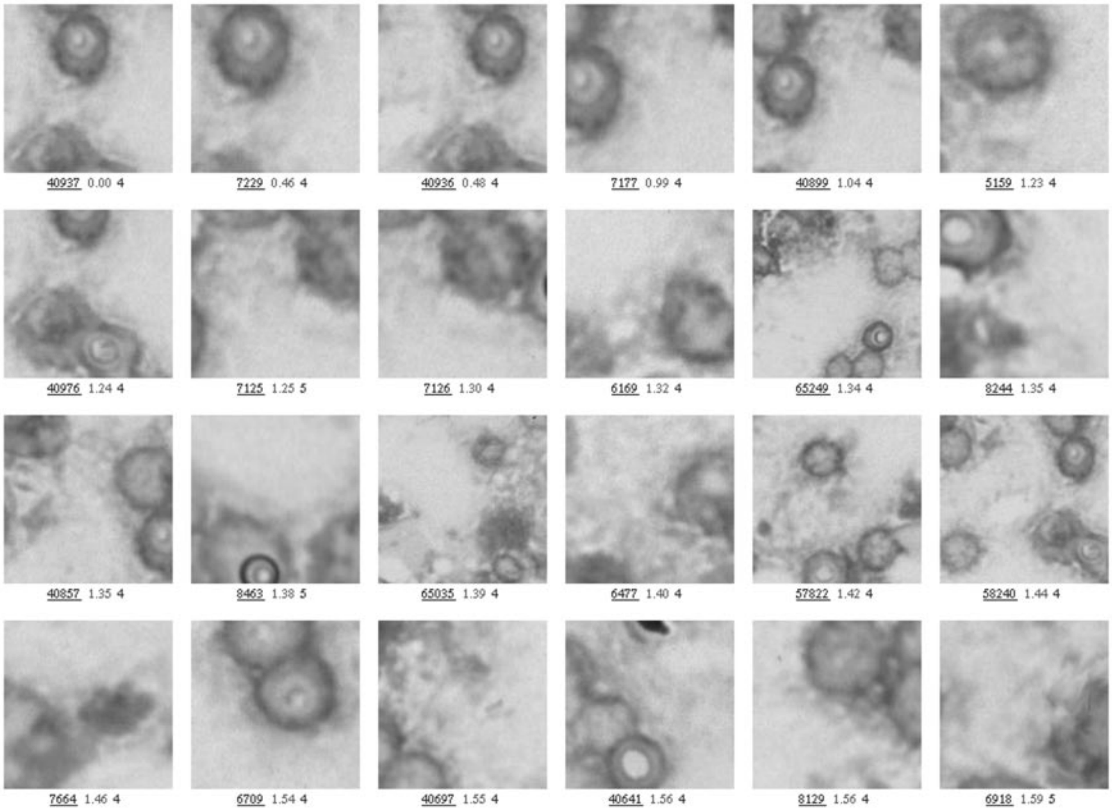


FIG. 8. A sample query result. The first image is the query.

McKeown, Chang, Cimino, and Hripcsak [22] of Columbia University plan to develop a personalized search and summarization system over multimedia information within a health care setting. Efficient CBIR is an important core technology within such systems.

CBIR can be applied to clinical diagnosis and decision making. Currently, more and more hospitals and radiology departments are equipped with PACS. Efficient content-based image indexing and retrieval will allow physicians to identify similar past cases. By studying the diagnoses and treatments of past cases, physicians may be able to better understand new cases and make better treatment decisions. Wong of the University of California at San Francisco has edited a book on the recent advances in the field of medical image databases [58].

CBIR can also be applied to large-scale clinical trials. As brain MRI image databases used in clinical research and clinical trials (e.g., for tackling multiple sclerosis) become larger and larger in size, it is increasingly important to design efficient and consistent algorithms that are able to detect and track the growth of lesions automatically. Brammer of the Institute of Psychiatry in London recently published their work on analyzing clinical trial functional MRI data [5]. In their experiments, they found that wavelet analysis was able to identify small signal changes against a noisy background and that most other techniques failed. By manipulating the wavelet coefficients in the spatial dimensions, activation maps can be constructed at different levels of spatial smoothing to optimize detection of activations.

Within bioinformatics, CBIR can be used for managing large-scale protein image databases obtained from 2-D electrophoresis gels. Presently, the screening process on very large gel databases is done manually or semiautomatically at pharmaceutical companies. With CBIR techniques, users may be able to find similar protein signatures based on an automatically generated index of the visual characteristics.

Finally, we can exploit CBIR in biomedical education. Medical education is an area that has been revolutionized by the emergence of the Web and its related technologies. The Web is a rich medium that can increase access to educational materials and can allow new modes of interaction with these materials. We may utilize CBIR to organize images of slides prepared for use in medical school pathology courses [53].

The Pathfinder system developed by Wang *et al.* at Stanford University [31, 54] is a multipurpose wavelet-based image retrieval system. It is based on the SIMPLIcity [51, 56, 57] content-based image retrieval system. It has proven effective in searching biomedical images such as digitized pathology slides. The Pathfinder system is a multiresolution region-based searching system. Experiments with a database of 70,000 pathology image fragments have demonstrated high retrieval accuracy and high speed. The algorithm can be easily combined with wavelet-based progressive pathology image transmission and browsing algorithms [53]. Figure 8 shows a sample query result. The user supplied a query with a round-shaped cell. The Pathfinder system successfully found images across different resolution, each with one or more round cells and similar visual characteristics, and ranked them according to their visual similarity to the query image. Figure 9 shows the result of a hand-drawn sketch query.

4. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, we reviewed a set of important mathematical tools for signal/image processing—the wavelet transforms, with emphasis on their applications in imaging informatics. Representative work has been identified in image compression, enhancements, analysis, classification, and retrieval. Compared to other tools such as the Fourier transform, the

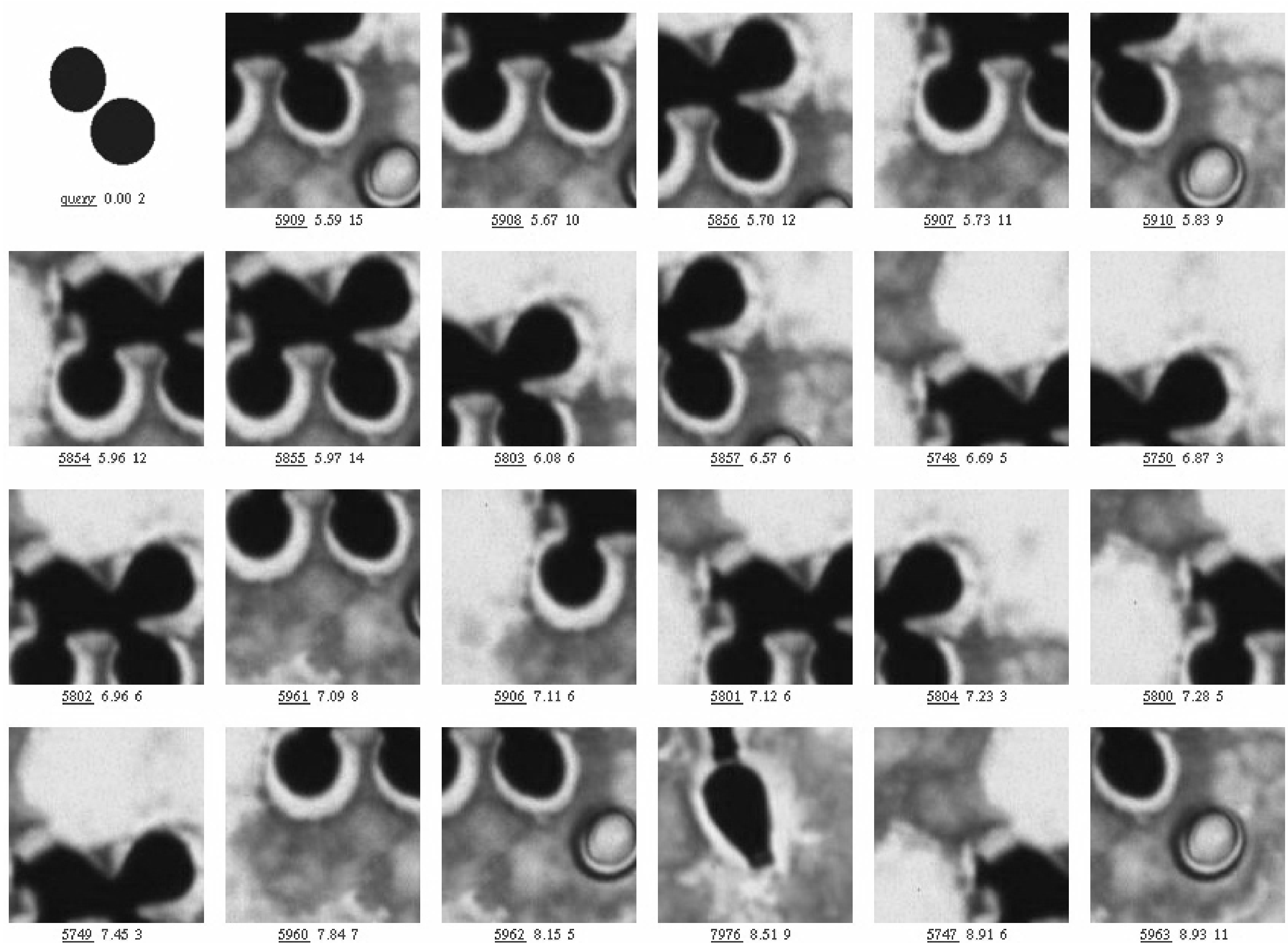


FIG. 9. The result of a hand-drawn sketch query.

wavelet transforms often provide better spatial domain localization property, critical to many imaging applications.

The application of wavelets to imaging informatics is only a decade old. Wavelets have demonstrated their importance in almost all areas of signal processing and image processing. In many areas, techniques based on wavelet transforms represent the best available solutions.

In the coming years, we expect to see more and more successful wavelet-based techniques in the field of imaging informatics. We expect hybrid schemes incorporating wavelets and other statistical techniques to achieve greater success. Theoretical research inspired by wavelets has led to new techniques such as ridgelet [6] and edgelet [24] transforms that are more promising in certain situations. Explorations on these new frontiers are likely to bring us more successful applications in imaging informatics.

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