Fingerprints Go Digital

Christopher M. Brislawn

The new mathematical field of wavelet transforms has achieved a major success, specifically, the Federal Bureau of Investigation's decision to adopt a wavelet-based image coding algorithm as the national standard for digitized fingerprint records [11, 4, 3].

The FBI standard, which uses an approach known as *wavelet transform/scalar quantization* (WSQ) image coding, was developed by project leader Tom Hopper of the FBI's Criminal Justice Information Services Division and Jonathan Bradley and Chris Brislawn from the Computer Research and Applications Group at Los Alamos National Laboratory. The standard, which is entirely within the public domain, involves a 2-dimensional *discrete wavelet transform* (DWT), uniform scalar quantization (a process that truncates, or "quantizes", the precision of the floating-point DWT output), and Huffman entropy coding (i.e., encoding the quantized DWT output with a minimal number of bits).

The FBI has a database consisting of some 200 million fingerprint records, stored (as they have been since the turn of the century) in the form of inked impressions on paper cards. As part of a modernization program, the FBI is digitizing these records as 8-bit grayscale images, with a spatial resolution of 500 dots per inch. This results in some 10 megabytes per card, making the current archive about 2,000 terabytes in size. (Note that a 3.5" high-density floppy disk holds "only" 1.5 megabytes.) Moreover, the FBI receives on the order of 30,000 new cards ($\equiv$ 300 gigabytes) *per day*, from all over the country, for background checks. After considering these numbers, the FBI decided that some form of data compression would be necessary and undertook a survey of the available image compression technology.

Transform-domain data compression is based on finding a signal representation, preferably one computable via a fast transform algorithm, that provides the ability to represent complicated signals accurately with a relatively small number of bits. This role has traditionally been filled by the Fast Fourier Transform and its related fast trigonometric transforms, particularly the discrete cosine transform [22]. Wavelets provide an important class of alternatives, however, whose properties make them particularly well suited for encoding high-resolution imagery, so let's briefly review the mathematical ideas behind wavelet transforms.

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Wavelets and Filter Banks

A wavelet series (or "multiresolution decomposition") is a scale-based decomposition of a signal into a linear superposition of dilates and translates of two special functions: a *scaling function*, ϕ, which carries the mean value and other low-frequency behavior of the signal, and a *mother wavelet*, ψ, which has mean 0 and encodes details of the signal from different length scales. Define subspaces in terms of the dilates and translates of these two functions:

$$V_j = \overline{\text{span}}\{\phi(2^j x - k) | k \in \mathbf{Z}\} \text{and}$$
$$W_j = \overline{\text{span}}\{\psi(2^j x - k) | k \in \mathbf{Z}\}.$$

The scaling spaces, V_j, generate a *multiresolution approximation* of $L^2(\mathbf{R})$,

$$V_j \subset V_{j+1} \nearrow L^2(\mathbf{R}),$$

and the wavelet spaces, W_j, "fill the gaps" between successive scales:

$$V_{j+1} = V_j \oplus W_j.$$

In particular, we can start with approximation on some nominal scale, say V_0, and then use wavelets to fill in the missing details on finer and finer scales:

$$L^2(\mathbf{R}) = V_0 + \bigoplus_{j=0}^{\infty} W_j.$$

Multiresolution analysis also holds the key to constructing scaling functions and mother wavelets: since $\phi \in V_0 \subset V_1$, it follows that the scaling function for a multiresolution approximation can be obtained as the solution to a 2-*scale dilational equation*,

$$\phi(x) = \sum_k h_0(k)\phi(2x - k), \tag{1}$$

for some suitable sequence of coefficients, $h_0(k)$. Once ϕ has been found, an associated mother wavelet is given by a similar-looking recipe:

$$\psi(x) = \sum_k h_1(k)\phi(2x - k). \tag{2}$$

Of course, some effort is required to produce appropriate coefficient sequences, $h_0(k)$ and $h_1(k)$; see [10].

A multiresolution decomposition describes a signal in terms of its "local averages" (the terms in V_0) and its "local details" (the terms in the W_j spaces), which are localized in dyadically scaled frequency "octaves" by the scale or resolution parameter, 2^j, and localized spatially by translation, k. The decomposition may or may not be orthogonal; in the nonorthogonal case (which includes the wavelet bases commonly used in image processing), we work with *pairs* of dual—or "biorthogonal"—bases:

$$\langle \psi_m, \psi'_n \rangle = \delta_{m,n}.$$

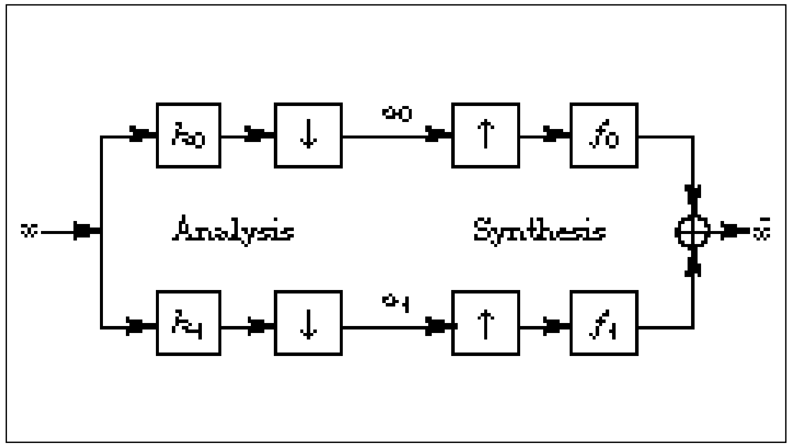

Figure 1. Two-channel mulitrate filter bank

While multiresolution analysis may still be an unfamiliar construction to many mathematicians, Littlewood-Paley theory [13] tells us that wavelet bases are actually ubiquitous and that multiresolution decompositions exist for many of the function spaces commonly encountered in analysis.

There is also a discrete version of multiresolution analysis for sampled data. Prior to the discovery of continuous wavelets, multiresolution transform methods had been studied in the field of digital signal processing under the name of *multirate filter banks*. Filter banks (parallel banks of digital convolution operators) provide fast, effective means of separating a digital signal into different frequency components. When the convolutional kernels are compactly supported (meaning *finite* supports in the discrete case), this frequency separation is accomplished using only *local* computations (as compared to nonlocal methods like the discrete-time Fourier transform).

The analysis half of the digital filter bank shown in Figure 1 contains lowpass and highpass filters, h_0 and h_1, followed by decimators, $\downarrow$, to divide the input into two *frequency subbands*. Decimation reduces the sampling rate of the filter outputs by discarding every other sample: $(\downarrow y)(n) = y(2n)$, the digital analogue of dilation-by-2. Note that each subband coefficient, $a_i(n)$, $i = 0, 1$, "feels" only a localized portion of the input, $x(n)$, as determined by the support of the kernel, $h_i(n)$. To put the signal back together, the original sampling rate is restored by interpolation, $\uparrow$, which inserts zeros into the subbands in place of the decimated samples, followed by more filtering and superposition of the subbands. If the filters are selected properly, this process produces zero distortion: $\tilde{x} = x$.

One of the big discoveries for both the wavelet and filter bank theories was that such distortion-

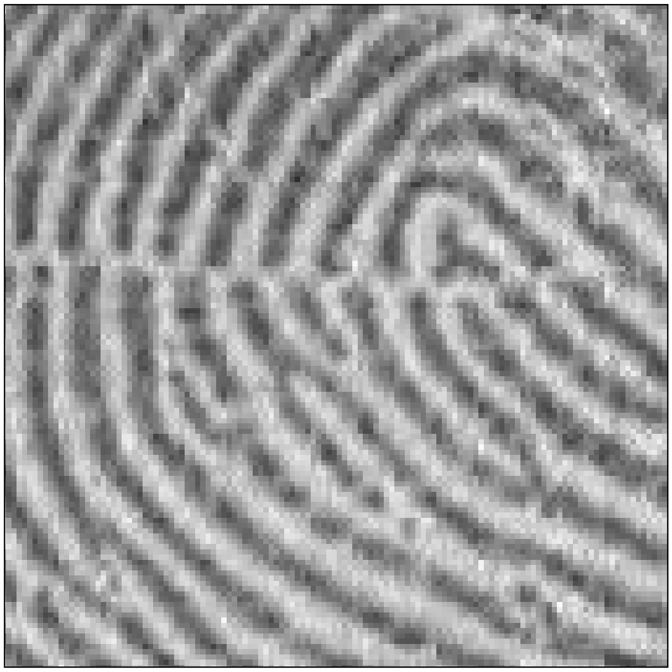

Figure 2. JPEG-compressed fingerprint image, 0.6 bits/pixel

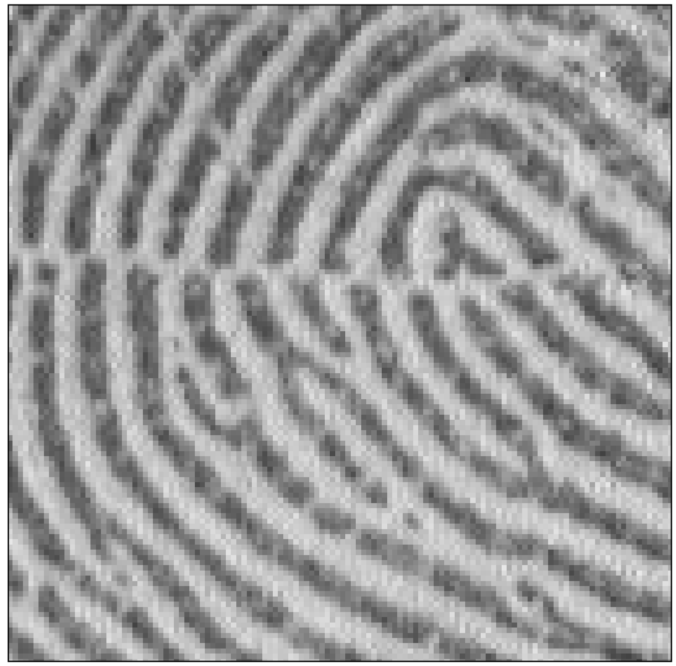

Figure 3. Original fingerprint image

free filter banks could be formed using the coefficient sequences, $h_0(k)$ and $h_1(k)$, from the 2-scale dilational equations (1), (2) for a multiresolution approximation. By cascading (i.e., composing) the analysis bank with itself a number of times, we can form a digital signal decomposition with dyadic frequency scaling, known as a *discrete wavelet transform* (DWT). The synthesis filters, f_0 and f_1, are given by the (time-reversed) analysis filters in the orthogonal case, or by the 2-scale coefficients of a dual scaling function and mother wavelet in the biorthogonal case.

The new twist that wavelets bring to filter banks is a mathematically rigorous connection between digital signal processing performed on sampled signals and an ideal analysis (i.e., a multiresolution series expansion) that one could in principle perform on the original, continuous signal. The combination of continuous wavelets and their corresponding discrete wavelet transforms provides a continuous/discrete duality for filter bank theory analogous to the quantitative and qualitative relationship between Fourier series and the discrete Fourier transform, without the restrictions imposed by the use of periodic functions.

Wavelet transforms were also discussed by Ingrid Daubechies in the January 1995 issue of the AMS *Notices*, so for the remainder I'll concentrate here on the story behind the new FBI standard. In addition to [10, 23, 20] and the other references cited in her article, the reader can find textbook expositions on the subject in [7, 1, 25, 28, 27, 14, 19, 26, 18] and compilations of survey and research articles in [2, 8, 9, 12, 24, 16, 17].

The FBI Fingerprint Standard

The first image coding algorithm considered by the FBI was the image compression standard drafted by the International Standards Organization's Joint Photographic Experts Group (known as "JPEG") [21]. The JPEG standard is based on partitioning a digital image into 8-pixel by 8-pixel blocks, applying a two-dimensional discrete cosine transform to each block, and compressing the output of each 8×8 discrete cosine transform. At even moderate compression ratios, however, the JPEG algorithm sometimes produces highly objectionable "tiling artifacts" resulting from boundary mismatches between the quantized low-frequency cosine modes in adjacent tiles; see Figure 2. For comparison, an uncompressed version of the original image and a WSQ-compressed version at the same bit rate as the JPEG example, around 0.6 bits/pixel, are shown in Figures 3 and 4. In addition to the lack of tiling artifacts in the WSQ image, note also the superior preservation of fine-scale details in the image, such as the sweat pores in the middle of the fingerprint ridges. (These are legally admissible points of identification!)

Transform coefficient quantization strategies tend to sacrifice high-frequency signal content in order to preserve more important low-frequency information, and if no space-frequency localization is imposed on a Fourier decomposition, the universal loss of

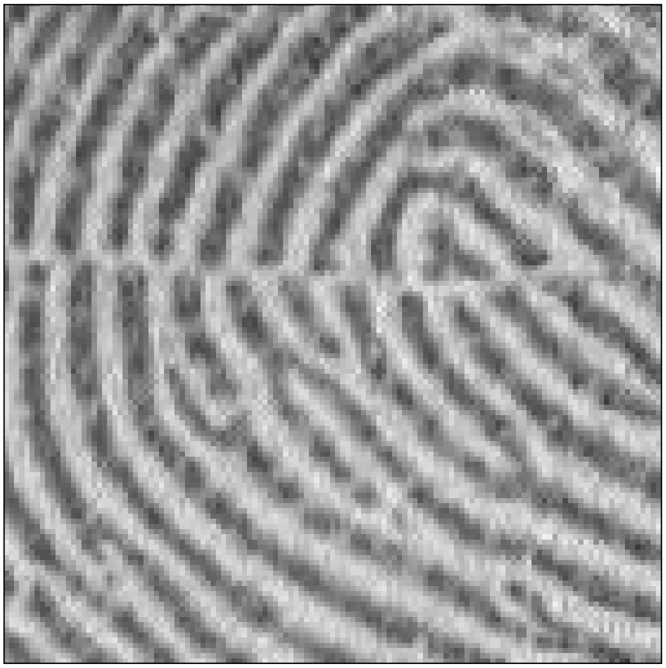

Figure 4. WSQ-compressed fingerprint image, 0.6 bits/pixel

high-frequency content due to coefficient quantization would result in objectionable Gibbs artifacts (known as "ringing" in image processing) and excessive smoothing of edges. (Fingerprints have a *lot* of edges.) Some form of tiling or windowing is therefore an unavoidable component of any Fourier-based image coding algorithm. Unfortunately, the tiling artifacts inherent in JPEG image coding are particularly vexatious in the fingerprint application because of the fact that the 8-pixel tiling frequency mandated by the JPEG standard is close to the natural frequency of fingerprint ridges in 500 dpi scans (take another look at Figure 2).

Based on testing by the FBI and the UK Home Office Police Research Group, it seems that JPEG tiling artifacts are unavoidable in fingerprint images at compression ratios above around 10:1, even with customized JPEG algorithms. Moreover, since these artifacts tend to appear suddenly and with high visibility as compression ratios are increased, the JPEG standard is not robust with respect to even slight overcompression errors, which can be expected in highly automated systems. Tiling artifacts are not only visually objectionable, but results obtained by Hopper and Preston [15] indicate that they also impair the performance of a key end-user for digital fingerprint images: automated fingerprint feature extraction ("minutiae detection") programs. These are computer algorithms that score prints for automated comparisons by tracing out fingerprint ridges and locating ridge endings and bifurcations, a process complicated by the sharp edges and corners associated with tiling artifacts.

In contrast, decompositions based on finitely supported digital filter banks achieve simultaneous space-frequency localization with no need for windowing. Instead of producing tiling artifacts at high compression ratios, image compression schemes based on filter bank decompositions degrade by losing resolution of high-frequency details in the image. This type of gradual blurring as the compression ratio increases is regarded by the FBI as a more graceful response to overcompression errors than the sudden appearance of pronounced tiling artifacts. Moreover, Hopper and Preston found that slight amounts of blurring do not adversely affect the performance of minutiae-detection programs.

Because of the unsatisfactory performance of the JPEG algorithm on fingerprints, the FBI investigated a number of alternative image coding methods. In addition to the JPEG standard, algorithms studied in [15] included a local cosine transform and an orthogonal Best-Basis wavelet decomposition, both developed at Yale University; an octave-scaled, four-level biorthogonal wavelet transform/vector quantization algorithm developed at Los Alamos; and a highly partitioned biorthogonal wavelet decomposition with scalar quantization (WSQ), developed by the FBI.

The local cosine transform algorithm had less pronounced tiling artifacts than JPEG but did not produce as high a degree of image quality as the three wavelet-based methods.The Best-Basis algorithm produced high image quality but took significantly longer to encode an image (a factor of 4 or 5 times longer) than the scalar or vector quantization algorithms, which produced comparably high image quality. In contrast to those two methods, which both use a fixed DWT decomposition on all images, the Best-Basis method constructs an optimal space-frequency decomposition (i.e., a "best basis") that minimizes an information cost functional for each individual image; see [28] for details. Incurring the additional cost of computing a fully adaptive space-frequency decomposition did not yield improvements in image quality, however, when compared to fixed, application-specific DWT decompositions. Similarly, vector quantization failed to produce improvements in rate-distortion performance over lower complexity scalar quantization. These results suggest that, at least for this application, there was little to be gained from using techniques more complex than a fixed DWT decomposition and adaptive uniform scalar quantization. Other experiments by the FBI indicated that there was also little or no advantage to using higher complexity arithmetic coding techniques versus the relatively simple Huffman coding algorithm.

Based on these findings, the FBI adopted a WSQ image coding standard, incorporating some of the better features of the Los Alamos wavelet/vector quantization algorithm. These include the use of symmetric extension methods to handle boundary conditions [5, 6] and an optimal weighted mean-square error quantizer design algorithm [3]. The optimal quantizer design is given by the solution to a nonlinear optimization problem subject to a (linear) constraint on the overall bit rate and (convex) nonnegativity constraints on the individual bit rates used to encode the DWT subbands. This gives the end-user effective control over the amount of compression imposed on an image and acts as a "quality knob" that can be set to ensure uniform quality in the compressed images. For instance, the FBI has discovered that images produced by older live-scan imaging systems (devices that scan the live fingertip rather than an inked impression on a paper card) are more sensitive to quantization noise than images produced by newer technology. The WSQ algorithm accommodates the older systems and still maintains high image quality standards by having them set their "quality knobs" to a lower compression ratio than newer imaging systems.

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The FBI specification [11] allows for the potential use of an entire class of different encoders; e.g., different wavelets or filter banks and different quantizer design strategies. The necessary filter coefficients, quantization parameters, and Huffman tables are transmitted as side information to allow a universal decoder to reconstruct images encoded by any compliant encoder. This will allow for future improvements in encoder design. So far, the FBI has approved just one encoder, employing a filter bank based on symmetric biorthogonal wavelets constructed by Cohen, Daubechies, and Feauveau [10]. Because of their connection to a basis of regular wavelets in the continuum limit, wavelet filters are particularly well suited for filter bank algorithms with many levels of frequency decomposition (the FBI standard uses five levels of analysis bank cascade in two dimensions, resulting in a 64-band decomposition). The compression target for this first-generation encoder is around 0.75 bits/pixel, which corresponds to about 15:1 compression on average fingerprint images.

Current effort is centered on implementing a compliance-testing program at the National Institute of Standards and Technology for certifying commercial implementations of the standard. Testing and certification is essential to ensure interchangeability of data between different implementations and to maintain consistently high image quality. In the future, we also expect digitization of the fingerprint database to facilitate advances in automated fingerprint classification. This is an area of research that has been greatly handicapped in the past by the use of paper-based fingerprint records.

Documents pertaining to the WSQ standard, as well as some sample fingerprint images, are available via anonymous ftp from Los Alamos, IP address `ftp.c3.lanl.gov`, in the directory pub/WSQ; a World-Wide Web link can be reached through `http://www.c3.lanl.gov/brislawn/main.html`.

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