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# Review of industrial applications of wavelet and multiresolution-based signal and image processing

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**Abstract.** *Twenty five years after the seminal work of Jean Morlet, the wavelet transform, multiresolution analysis, and other space-frequency or space-scale approaches are considered standard tools by researchers in image processing. Many applications that point out the interest of these techniques have been proposed. We review the recent published work dealing with industrial applications of the wavelet and, more generally speaking, multiresolution analysis. We present more than 190 recent papers.*  [DOI: 10.1117/1.2957606]

## 1 Introduction

The wavelet transform is already an old concept for signal and image processing specialists. It has now been 25 years (1982) since Jean Morlet, a French engineer working on seismological data for an oil company, proposed the concept of wavelet analysis to automatically reach the best trade-off between time and frequency resolution.[57,116] Later, this proposition was considered a generalization of ideas promoted by Haar (1910) and Gabor (1946),[50] themselves followers of Fourier (1888). As with any discovery in science, wavelets resulted from numerous contributions and are based on concepts that already existed before Morlet's work. Clearly, it was in the air in the signal processing community in the 1980s. Shortly after this seminal proposition, the main elements were fixed by Meyer (1985),[110] Mallat (1987),[105] and I. Daubechies (1988).[37] Numerous other contributors cast their stone in the 1990s. Among them, a special mention to the lifting scheme and the second-generation wavelets proposed by Sweldens (1995)[152] should be given. Even more recently, some very exciting papers have been published about new ideas (ridgelets,[24,25,39] curvelets,[41] contourlets, and other X-lets). These concepts show that the subject is still alive and a rich ground for innovative propositions to blossom. The wavelet transform, multiresolution analysis, and other space-frequency or space-scale approaches are now considered standard tools by researchers in image processing; many applications have been proposed to exploit the interest of these techniques. The wavelet analysis algorithm is included in every signal processing computing package, and most undergraduate students in computer engineering have had some courses on the subject. The most known application field of the wavelet transform is image compression for still and video image transmission. This tool is included in the new norms of JPEG and MPEG, where it replaced the classical discrete cosine transform. In audio and, more precisely, automatic speech analysis, wavelets are currently in operational software. However, even if promising practical results in machine vision for industrial applications have recently been obtained, the wavelet transform in operational industrial products is still rarely used, and, too often, space-scale processing tools fail to be included in industrialist imaging projects. The reason may be the, sometimes abstruse, mathematics involved in wavelet textbooks or the false faith in the omnipotence of this new approach, leading to disappointing experiences. Be that as it may, it seems more necessary than ever to propose opportunities for exchanges between practitioners and researchers about wavelets. In this respect, this paper aims at reviewing the recent published work dealing with industrial applications of the wavelet and, more generally speaking, multiresolution analysis. In the first part, we recall the basics of wavelet transform and of its main variations in a simple overview. In the second part, some of its applications are reviewed in each domain, beginning with signal processing and continuous and discrete wavelet transforms, and then proceeding with image processing and applications. More than 190 recent papers are presented in these two sections. This article is a new version, revised and completed, of a review presented by the authors during a session of the SPIE Conference, Optics East 2004, dedicated to industrial applications of wavelets.[160,162,163]

## 2 Wavelet Transform Basics

Basically, as a short-time Fourier transform (STFT), the wavelet transform (WT)[106,159,166,170] is a means of obtaining a representation of both the time and frequency content of a

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signal. But, in WT, the window function width is dependent on the central frequency. Therefore, for a given analysis function, the best trade-off between time and frequency resolution is automatically obtained and kept. A wavelet is a kernel function used in an integral transform. The wavelet transform (CWT) of a continuous signal $x(t)$ is given by

$$W_{a,b}(x) = \int_{-\infty}^{+\infty} x(t)\psi^*_{a,b}(t)dt,$$

with the wavelet function defined by dilating and translating a "mother" function as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right),$$

where $\psi(t)$ is the "mother" wavelet, $a$ is the dilation factor (a real and positive number), and $b$ is the translation parameter (a real number). If the wavelet function is well chosen, it is said to be admissible, and computing the original function from its wavelet transform is possible:

$$x(t) = \int_{0}^{+\infty}\int_{-\infty}^{+\infty} W_{a,b}(x)\psi_{a,b}(t)\frac{dadb}{a^2}.$$

If the wavelet is reasonably localized, the admissibility condition is simply

$$\int_{-\infty}^{+\infty}\psi(t)dt = 0.$$

For practical reasons, the dilation and translation parameters are often discretized, leading to the so-called discrete wavelet transform (DWT). After discretization, the wavelet function is defined as

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t-k). \quad (1)$$

As for the CW, the DWT is given by the inner product between the signal and the wavelet. The result is a series of coefficients:

$$d_x(j,k) = \langle x, \psi_{j,k}\rangle,$$

where $j$ and $k$ are integer scale and translation factors. Mallat,[105] Daubechies,[37] and, in another manner, Sweldens[152] gave way to a fast algorithm implementation of DWT (the only one to be in use for computer imaging applications). The wavelet transform is a very efficient tool for scale-time (or scale-space in imaging applications) signal analysis, characterization, and processing. Its scale discrimination properties are widely used for practical applications in algorithms of denoising (selective coefficients thresholding), scale filtering (different from classical frequency filtering), fractal analysis, or scalogram visualization. Its capability to organize and concentrate information is also one of the main reasons for the WT's success in image compression.

## 3 What Transform, with Which Wavelet?

The CWT leads to a continuous representation in the scale-space domain. It allows a fine exploration of the signal behavior through a scale range but is a highly redundant representation. The reconstruction process (inverse transform) is generally a very time-consuming task. Therefore, the CWT is used mainly for 1D signal processing and when no synthesis is required. For images, and if the original signal is to be reconstructed after analysis, one prefers the DWT and generally its simple dyadic version presented in Eq. (1). The DWT can be performed in a nonredundant scheme following the decimated algorithms proposed by Mallat[106] or Sweldens[152] or, if translation invariance is necessary, in a redundant algorithm (nondecimated or "a-trous" algorithm). The wavelet set can constitute an orthogonal basis or, relaxing some constraints, a bi-orthogonal basis or even a simple frame. More generally, the choice of the wavelet kernel is driven by some properties to be verified. The most important and commonly considered properties are the regularity, the number of vanishing moments, and the compactness. The regularity or number (integer or not) of continuous derivatives indicates how smooth the wavelet is. Its localization in the frequency domain is directly connected to this regularity: the larger the regularity, the faster the decrease in Fourier space. The number of vanishing moments is linked to the number of oscillations of the wavelet (localization in space). More importantly, if a wavelet has $k$ vanishing moments, it kills all the polynomials of degree equal to or lower than $k$ in a signal. The size of the wavelet's support is also an important issue: the longer this support, the higher the computational power required for the WT. The maximum number of vanishing moments is proportional to the size of the support. If a wavelet is $k$ times differentiable, it has at least $k$ vanishing moments. Therefore, a trade-off between computational power and analysis accuracy and between time resolution and frequency resolution must be achieved in each given problem. Table 1 gives some examples of the regularity, number of vanishing moments, and support size for some popular wavelets (Haar, Daubechies wavelet).[37]

**Table 1** Properties of some popular wavelets.

| Wavelet | Haar | Db2 | Db5 | Db10 |
|---|---|---|---|---|
| Regularity | NA | 0.5 | 1.59 | 2.90 |
| Vanishing moments | 1 | 2 | 5 | 10 |
| Support size | 2 | 4 | 10 | 20 |

In the following sections, more than 190 examples of applications are reviewed by application domains and from signal analysis to image processing. Many kinds of wavelet transforms and wavelet basis are involved. The main contributions of the wavelets are their capability to provide time-scale analysis (scalograms, transient detection and characterization, feature extraction) or multiscale analysis (characterization of fractal behavior, texture analysis) and to organize information in a signal (compression), and the reversibility of the WT (for filtering and denoising).

## 4 Signal Processing Applications

### 4.1 Acoustical Signal Processing

Applications of the 1D WT are numerous in acoustical signal processing. Kobayashi[86] presents some examples of WT-based acoustical signal processing techniques proposed by Japanese researchers for listening for defects in automated quality-control mechanisms. Analyzing detonation signals in automobile engines by CWT (Gaussian-type wavelet)-based scalogram and phase shift display[85] or using the same technique to detect irregularities in cement mixtures (sound emitted by the barrel spinning on a cement truck)[6] are just two examples of these techniques. Abbate applies the wavelet transform (WT) to the time-frequency analysis of ultrasonic echo waveform obtained by an ultrasonic pulse-echo technique.[2] The Gabor function is adopted as the analyzing wavelet since it provides the best time-frequency resolution, as confirmed by the uncertainty principle. In this study, noise suppression by thresholding of the ultrasonic flaw signal and nondestructive evaluation (NDE) of material degradation using wavelet analysis of an ultrasonic echo waveform have been verified experimentally. Ultrasonic waves are one promising method for the nondestructive inspection of pipeline integrity. Discriminating between normal features (welds) and serious flaws (cracks or corrosion) can be facilitated by wavelet analysis (energy and entropy of wavelet coefficients at various scales), as shown by Tucker *et al.*[165] Evaluation of degradation and damage of thermal sprayed coatings can also be performed in a nondestructive way by ultrasonic testing. The WT (DWT Daubechies of order 10) can be used to analyze the ultrasonic waveform for enhancing the signal-to-noise ratio by maintaining a scale of 3.[63] In a closed domain, speech enhancement is also an interesting challenge for wavelet users. Removing environmental noise by different approaches using the DWT[58] and coefficient thresholding (wavelet shrinkage[40,140]) or Wiener filtering in the wavelet domain[107] were both successfully tested, as was the blind equalization in the wavelet transform domain for speech analysis.[119] The estimation of subsoil characteristics and physical properties is a very important task in various fields (geology, risk evaluation before a building construction, petroleum exploration). After propagation in the subsoil, the induced seismic disturbances are recorded by a set of sensors regularly placed on the ground. By analyzing the recorded signals, different waves can be identified (surface waves, reflected waves, etc.). The estimation of the physical properties of these waves (delay, speed) leads to an estimation of the structure of the subsoil.[133] Processing and characterization of 3D seismic data for the petroleum industry by classical CWT are proposed by Yin *et al.*[191] or by using wavelet constructions based on the acoustic wave equation (physical wavelets[78]), by Wu *et al.*[185] Numerous other references dealing with the same topic can be found in *Oil & Gas Journal*.

### 4.2 Power Production and Electronic Power

Electronic power and the control of rotating and other electric machines are investigated with the WT.[35,129] Aller *et al.* proposed a sensorless speed estimate using an analytic wavelet[106] (constructed by modulating the frequency of a real symmetric window) transform. These computations are performed in the Fourier domain with the FFT of the current signal. The instantaneous frequency is determined from ridge detection in the scalogram.[8,94,101,102] Zonardelli *et al.* presented methods to identify developing electrical and mechanical faults in permanent-magnet AC drives based on both the short-time Fourier transform and wavelet analysis of the field-oriented currents in permanent-magnet AC drives.[193] The different fault types are classified by developing a linear discriminant classifier based on the transform coefficients. Power-quality monitoring consists mainly of detecting harmonic and voltage disturbances. Antonino-Daviu *et al.* proposed a method for the diagnosis of rotor bar failures in induction machines, based on the analysis of the stator current during the startup using the DWT.[12] Unlike other approaches, the study of the high-order wavelet signals resulting from the decomposition is the core of the proposed method. If the Fourier transform is currently used to analyze distorted waves in the frequency domain, Tsao[164] has shown how the WT and probabilistic neural network can help to achieve such an analysis in real time. The application of wavelet analysis on power system transients has become increasingly popular in recent years due to its effectiveness in capturing short-term transients. Power production (synchronous generators) and delivery disturbance surveys are the main targets. High-voltage insulation suffers from aging processes, and failure can be sudden and catastrophic. Online monitoring and processing of electrical signals can provide useful diagnostic information. Transient detection, localization, identification, and classification are the objects of the processing. They apply to power transmission lines[52,80,147,153,186,190] but also to the faulted phase current from a generator. One example of transient detection and analysis aided by producing scalograms with a CWT using a pair of phase complementary wavelets that allow phase information arising from the wavelet transform can be found in Ref. 36. There are many other papers on the same application.[131,135] More generally speaking, Kareem and Kijewski overview recent developments in wavelet-based analysis of a number of physical processes of relevance to the civil engineering community.[82] For example, the extension of wavelet transforms to the estimation of time-varying energy density permits the tracking of evolutionary characteristics in the signal using instantaneous wavelet spectra and the development of measurements like wavelet-based coherence to capture intermittent correlated structures in signals.

### 4.3 Nondestructive Testing (NDT)

In the work of Barat *et al.*,[15] Batko and Mikulski,[16] or Mikulski,[111] steel wire rope testing is performed. The diagnostic signal of steel wire rope by magnetic flux leakage (MFL) testing consists of impulses with different magnitudes and durations depending on the depth and dimension of the wire defects. However, all such impulses have approximately the same form caused by distribution of the magnetic flux leakage around a broken wire. This particular feature allows one to suppose that application of the wavelet transformation for the purpose of signal analysis can significantly increase the sensitivity and reliability of defect detection. Indeed, good results in terms of diagnosis reliability can be achieved using a weighted summation of wavelet values for some chosen scales. In particular, the authors calculate a value that reflects the relationship between useful impulse energy and interference energy for different wavelet types (namely, the square root of this relationship). This relationship shows that the Haar wavelet gives a dramatic improvement in the SNR. Another NDT application is the processing of the signal given by an MFL from a ferromagnetic material surface after magnetization, as in the magnetic flux leakage test of oil and gas pipelines. Yang-Lijian *et al.* use bi-orthogonal wavelets to decompose actual signals; the results show that the wavelet analysis performs well in the feature extraction of flux leakage signals of the pipeline.[188,192] In a more general approach, Kurz *et al.* proposed a brief review of the major wavelet algorithms involved in nondestructive testing.[90] They point out filtering and denoising by wavelet shrinkage in particular. Parts inspection is also investigated by wavelet analysis. Tool wear monitoring can be performed by extraction of feature vectors from vibration signals measured during machining (DWT, energy of coefficients at each scale from orthogonal Daubechies of length 6 with 6 levels). Turning operation is selected by Wang *et al.*[16] as an example. Other authors have proposed similar approaches.[56,69,70,74,79,92,115,118,122,124,128,150,173,174,175] Wu *et al.* proposed a method for real-time tool condition monitoring in transfer machining stations.[184] This tool condition monitoring is obtained indirectly by online fine analysis of the spindle motor current. This fine analysis consists of calculating the wavelet packet transform of the signal and selecting the principal components. The analysis of the gas turbine vibration can be enhanced by the use of wavelet characterization and the Wigner–Ville distribution, as has been proposed.[62] It is the ability to zoom in on short-lived high-frequency phenomena that makes the WT particularly attractive for the analysis of transients. The output of vibration sensors is digitized and fast transient features are characterized from the evolution of the wavelet transform coefficients across distinct scales. A neural network is used to extract the monitoring information. Computer simulation is an essential part of the design and development of jet engines for the aeropropulsion industry. Wavelet techniques are very suitable for analyzing the complex turbulent and transitional flows pervasive in jet engines. These flows are characterized by intermittency and a multitude of scales. Wavelet analysis results in information about these scales and their locations. Turbulent flow modeling in turbomachinery has been particularly developed by the NASA Lewis Research Center.[61,95] Process control can benefit from the WT.[149] Parvez and Gao[125,126] have proposed a PID-like controller based on a wavelet analysis of the error signal. This analysis allows high-frequency and low-frequency components to be extracted and used for optimally adapted control signals for the nature of error. Two examples of control, motion and temperature, are given. Symlets and Daubechies of order 4 were found to be reasonably good tools for control. Wavelet neural networks[55] have been found very effective for the control of industrial processes. Localized modeling and compression of key process-relevant information, especially information pertaining to the detection of equipment and process faults in the IC industry, is one example.[134] Rying, in his Ph.D. dissertation, also presents a novel application of the wavelet transform modulus maxima representation to help determine and prioritize the set of local features as a signal for monitoring the film thickness during growth of silicon epitaxy coming from a quadrupole mass spectrometer sensor.[134] Another application of these neural networks is proposed by Gao *et al.*[51] for flow measurement with a neural wavelet-based analysis of a magnetic flowmeter (an instrument for measuring the flow velocity in many industrial applications) signal.

### 4.4 *Chemical Process*

In the chemical industry, signal processing and control is widely used and the WT appears naturally as a useful tool.[9] For instance, Aballe *et al.*[1] investigate the validity of wavelet analysis as an alternative procedure to process electrochemical noise records (ENR), especially those in which different signals are superposed. They measure the energy at different scales or separate two components of the signal (high coefficients for one component and the remaining for the other one) by the inverse wavelet transform. Chemical process survey by filtering of process variables as a time series (cubic-spline wavelets) is presented by Schrötter and Lieden.[138] Briesen and Marquardt[21] present a chemical process modeling by the adaptive multigrid method on the basis of a wavelet–Galerkin discretization for the simulation and optimization of processes involving complex, multicomponent mixtures in the petroleum industry. Close to this domain of application, one can notice an interesting attempt to use radial wavelet networks[196] (a variety of neural networks using a wavelet transform to determine the weights, as the Gaussian functions are used in radial basis functions, RBF) for modeling the relationship between the chemical composition of steel and its hardness profile.[33,34]

### 4.5 *Intelligent Transportation Systems*

Wavelet analysis and transforms appeared as common processing tools for the emergent domain of intelligent transportation systems. The WT is used for feature extraction for traffic incident detection, representation of traffic patterns, traffic flow prediction,[151] or even material characterization (pavement study[146] and structural damage survey). The WT in the discrete or continuous form is involved in detecting singularities, denoising, and detecting long-term trend analysis self-similarly.[7,197] A comprehensive review of these applications has been recently released by Adeli and Karim.[7]

### 4.6 *Stochastic Signal Analysis*

The future shows great promise for the wavelet as a tool to redefine the probabilistic and statistical analysis of the numerical series.[23,112,127] As in Ref. 120, where wind speed is modeled at a target location from the wind speed and direction known at a reference location (given by a time series) with a nondecimated wavelet packet transform to model the explanatory time series. The proposed technique transforms the explanatory time series into a wavelet packet representation and uses standard statistical modeling methods to identify which wavelet packets are useful for modeling the given time series. Applications in economics and finance[44,53] are another use of the WT's properties. For example, Gencay *et al.*[53] use the wavelet multiscaling approach to decompose a given time series on a scale-by-scale basis. At each scale, the wavelet variance of the market return and the wavelet covariance between the market return and a portfolio are calculated to obtain an estimate of the systematic risk. The WT is used as a key tool for unraveling the mysteries of computer traffic statistics and dynamics. Scale-invariant properties such as long-range dependence and self-similarity are estimated from squared wavelet coefficients averaged over time, as in Refs. 4, 43, and 137: "The impact of scale invariance extends to network management issues such as call admission control, congestion control, as well as policies for fairness and pricing."[3] In this area, a multifractal wavelet model has been proposed and applied to network traffic modeling and inference.[4] The capability of the WT for the analysis and synthesis of long-range dependence signals has been investigated.[130] One can find a lot of other applications of the wavelet transform, and nearly every signal processing-based device can be infected by a WT. Wavelet-based communication systems, for example, are a promising design involving wavelet packet transforms to obtain a given time-frequency partitioning.[100] Applications in bioinformatics also have great potential. We will review some of them in Section 5.4. We could cite many other examples.

## 5 Image Processing Applications

### 5.1 *Image Compression*

Image compression is the main application of the WT in image processing. The wavelet compression algorithm provides better compression quality than the traditionally used JPEG algorithm.[67,87,132] The current international standard for image compression (JPEG 2000) is largely based on a scalar quantization of the coefficients of a DWT performed with Daubechies bi-orthogonal bases. Many authors have contributed to the field. One can find the forerunners and comprehensive papers among the following references: 11, 38, 99, 109, 142, 155, 167, 194, and 195 (JPEG 2000 coverage from two of the members of the JPEG Committee has to be noted.[156] Incidentally, the wavelet-based image compression has an error that is different for even and odd-pixel locations, which has been recently analyzed and formally addressed.[97] It is to be noted that besides JEPG 2000, there also exist some proprietary compression systems based on the wavelet transform, the most frequently used and known being MrSID and DjVu. They are proposed in commercial products such as security cameras or video survey systems. Even multispectral images (from satellite imagery, for instance) can be compressed with a wavelet-based method with multiwavelets, for one instance.[77] One of the earlier and most celebrated applications is the digital fingerprint image compression wavelet-based standard adopted by the FBI in 1993 (to store its 200 million fingerprint records, representing about 2,000 terabytes).[20,32] It is based on a simple scalar quantization of the 64-subband wavelet coefficients (bi-orthogonal wavelets of Cohen–Daubechies–Fauveau, 1990) and leads to good-quality images with a compression ratio of about 20:1.[22] Video compression is a natural extension of the previous results.[26,31,59,60,154,157,177] Still imaging and video compression techniques based on the WT are widely used in digital video recording, such commercial products are available for video monitoring or surveillance. These products make use of dedicated commercial software (see Ref. 71 for one example among numerous others), hardware (see, for instance, the PCI Bus-mastering wavelet video compression/decompression and capture board from XPress Plus: http://www.jknelectronics.com/xprspls1.htm), or even of the integrated wavelet video codec,[42] now proposed by most IC producers.[195] The implementation can also be performed with dedicated hardware based on the use of integrated digital signal processors.[47] Generally speaking, the most successful application for the wavelet transform is image compression and JPEG 2000. But JPEG 2000 is very difficult to popularize in the industry currently, partly due to the lack of compatibility with JPEG. So wavelet-based compression is often used in a fresh field such as digital film, which needs an extremely high visual quality. A possible development is the multibank wavelets in image or video compression, for it is closer to the currently used transform. For example, the discrete cosine transform is just a special 8-bank wavelet. The multibank wavelets have the orthogonality and linear phase. An excellent paper is that of Wang, which systematically studies the 4-bank wavelets.[172] Strongly linked to image compression and transmission, digital image watermarking is an important issue in which the WT plays its part. Invisible and robust data hiding or embedding takes place in the spatial as well as the frequency domains. Vandergheynst *et al.* show how directional wavelet frames can be used for computation of isotropic measuring of local contrast, which is used as a masking model to facilitate the insertion of a watermark.[113,169] Ghouti *et al.* proposed a robust watermarking algorithm using a balanced multiwavelet transform.[54] The latter transform achieves simultaneous orthogonality and symmetry without requiring any input prefiltering. Therefore, considerable reduction in computational complexity is possible, making this transform a good candidate for real-time watermarking implementations such as audio broadcast monitoring and DVD video watermarking.

### 5.2 *Satellite Imagery*

As high-resolution imagery becomes commercially available, satellite imagery in geospatial applications is quickly spreading in the civil industry. As Morley[117] points out, wavelet technology is now the "state of the art" for image compression that eliminates (or at least drastically reduces) the trade-off between size and quality. The 3D wavelet transform is used for denoising and processing spatial and spectral data from Landsat images with application to surveillance of deforestation and crop detection.[75,76] Geographic information systems (GIS) increasingly use it as a tool for topographical applications. Research takes advantage of the WT for modeling complex multivariate geographic relationships. Morehart *et al.*[114] have shown with examples from agricultural data that the redundant "a trous" algorithm aids enormously in feature detection and exploration in the succession of resolution views of data. Brunsell and Gillies say, "Recent research[89] suggests that wavelet decompositions are powerful tools in analyzing the scaling behavior of geophysical variables (statistical variation of signal across different resolutions)." Hu *et al.*[64] use multiresolution to study the scale variation of soil moisture; average large-scale and detailed small-scale fluctuation components are extracted from the WT.

### 5.3 *Machine Vision*

Aspect inspection is one of the main industrial application issues of digital image processing.[93] Karras *et al.*'s suggested solution focuses on detecting defects for manufacturing applications (in the design of robust quality-control systems for the production of furniture, textiles, integrated circuits, etc.) from their wavelet transformation and vector quantization-related properties of the associated wavelet coefficients.[81,104] More specifically, they investigate a novel methodology for discriminating defects by applying a supervised neural classification technique, namely a support vector machine, to innovative multidimensional wavelet-based feature vectors. These vectors are extracted from the *k*-Level 2D DWT (discrete wavelet). West and Williams explain that the needs of industrial process tomography can be markedly different than those of other disciplines.[180] Some of these differences (far greater automation and quantification will be required) are illustrated in their hydrocyclone case study. They cite most of the authors using wavelets to fuse data at different levels. The technique of imaging secondary ion mass spectroscopy (SIMS) is largely used in chemistry to analyze and characterize location and quantitative distributions of chemical components. Nikolov *et al.* proposed using the wavelet shrinkage algorithm to denoise those images and improve their interpretation[121,183] Texture characterization is a well-fitted problem for wavelet analysis.[168] Lumbreras *et al.* proposed, for instance, combining color and texture information through a multiscale decomposition of each color channel in order to feed a classifier.[103] Three algorithms are tested: multiresolution analysis with Mallat's algorithm, the *à trous* algorithm,[148] and the wavelet packet transform. Two applications are presented: the sorting of ceramic tiles and the recognition of metallic paints for car refinishing. The application of wavelets to processes and issues critical to semiconductor manufacturing is a promising challenge. Real-time inspection in microelectronics manufacturing with multiresolution imaging is proposed by Bourgeat *et al.*[19] The paper industry is also involved in using the WT, as Huawei showed through his studies of fiber flocculation (a disturbing phenomenon for paper formation) and its parameters by processing stacks of images taken by high-speed video camera; the images were treated by a 2D CWT Mexican hat wavelet before correlation to the original ones.[65,66] Another one of the few continuous wavelet transform applications in image processing using the wavelet transform modulus maxima method is proposed by Arneodo for analyzing the fractal properties of a textured image.[13] Westra uses this method for printing defect identification and classification (applied to printed decoration and tampoprint images) with a template-invariant approach.[181,182] Texture and feature analysis by the WT are also used in image database retrieval algorithms.[68,72,108] Yang *et al.* proposed an image browsing technique for infomediaries.[189] Their system offers a dynamic mechanism for organizing product images by their features in terms of colors and textures. The textural features are extracted from the luminance component of color images using Gabor filters. They show that the retrieval accuracy of the filters is higher than other textural features, such as the conventional pyramid-structured wavelet transform (PWT) features, the tree-structured wavelet transform (TWT) features, and the multiresolution simultaneous autoregressive model (MR-SAR) features. Addis *et al.* present an updated technical overview of an integrated content and metadata-based image retrieval system used by several major art galleries in Europe, including the Louvre in Paris, the Victoria and Albert Museum in London, the Uffizi Gallery in Florence, and the National Gallery in London.[5] Texture matching is based on energy coefficients in the pyramid wavelet transform using Daubechies wavelets. Other wavelet decompositions and basis functions are implemented and compared along with Gabor filter banks, but the incorporated approach was chosen as the best compromise between retrieval accuracy and computational efficiency. Face recognition algorithms have now demonstrated their efficiency. Karibasappa and Patnaik developed a method for face recognition based on the wavelet transform.[83] They use the "symlet" wavelet because of its symmetry and regularity. The wavelet coefficients are the features to be used for image classification. The fabric industry has room for quality control by artificial vision and wavelets in that their ability to characterize textured features are a precious processing tool.[73,187] In the framework of the textile industry,[27,96] Sarri-Saraf *et al.* present a device aiming at online inspection of the loom under construction.[136] A specific class of the 2D discrete wavelet transform called the *multiscale wavelet representation* is used as a preprocessing step with the objectives of attenuating the background texture and accentuating the defects. The non-subsampling properties guarantee the accuracy of detection and classification that follows. In the same application domain, Serdaroglu *et al.* proposed performing an independent component analysis on a subband decomposition provided by a 2-level DWT in order to increase the defect detection rate in an online fabric inspection device.[141] An application of the WT in plastics manufacturing has been proposed by Laligant.[91] Plastic caps are imaged; the internal thread by taking advantage of its periodical and localized features is controlled in the wavelet domain. Even applications in agriculture can be found. For instance, for weed detection from airborne imaging, an automatic herbicide sprayer is developed in order to reduce herbicide application amounts for corn and soybean fields.[158,171] Detailed wavelet coefficients corresponding to weed frequencies and orientations are selected in a discrete wavelet transform and thresholded. In another example dealing with the same application field, the DWT with Daubechies wavelets is retained for compression of spectral data by Okamoto *et al.*[123] in order to achieve a classification among crops (sugarbeet), soil, and various weeds (wild buckwheat, field horsetail, green foxtail, common chickweed). In this case, the importance of a wavelet coefficient is defined by the accumulated energy rate of the coefficients sorted in the average energy. After selecting the most effective wavelet coefficients, the authors proceed with a statistical linear discriminant analysis.

### 5.4 *Bioinformatics*

Applicaitons can be found in biology or in what is now called *bioinformatics*. DNA sequence analysis is a huge challenge involving a lot of signal and image processing in which the ability of the WT to perform good localization both in frequency and in space is of great interest. Chang *et al.* introduce a contrast and aberration correction image fusion method, for reading the fluorescent intensity distribution of two wavelengths for the same hybridization DNA sequence spot, by using the discrete wavelet transform to two wavelength identification microarray biochips.[28] Kawagashira proposed a method called the "wavelet profile" based on multiresolution analysis.[84] Protein sequences represented numerically by different indices (polarity, accessible surface area, electron-ion integration potentials of the amino acid) can be decomposed by the WT and upsampled for similarity searching across scales and different proteins.[88] The gene array experiments in Ref. 178 involve a large number of error-prone steps, which lead to a high level of noise in the resulting images. The authors use the shrinkage approach based on a stationary wavelet transform for eliminating such noise sources and to ensure better gene expression. More generally speaking, the stationary transform facilitates the identification of salient features, especially for recognizing noise. The universal image quality index[179] highlights the superior results of the stationary transform compared to the downsampled one and gives performances with respect to the wavelets used (Haar, Daubechies, bi-orthogonal, Coifman, etc.) Even classifying images as objectionable or benign can be aided by the wavelet transform (Daubechies), as Wang *et al.* showed.[176] An original application in forensic science has been proposed in order to discriminate natural images from synthetic ones. It makes use of a statistical model built upon a multiscale wavelet decomposition.[46]

### 5.5 *Flow Analysis*

Image processing is also used to analyze turbulent flows, and wavelets appear here as well. Li *et al.* apply the vector wavelet multiresolution technique to analyze the three-dimensional measurement results of a high-resolution, dual-plane stereoscopic particle image velocimetry system for revealing a fundamental understanding of the multiscale vertical structures in the near field of a turbulent lobed jet.[98] The authors chose the Daubechies wavelet basis for its smoothness and compact support. The instantaneous three-dimensional velocity is calculated and interpreted in multiscale velocity fields.

Although they cannot be extensively cited in this paper, many other application fields of the WT dealing with less industrial topics such as optical aberration analysis[29,143–145] and optical testing[30] and, more generally speaking, scientific data analysis exist.

## 6 Conclusion

As shown in this, still largely incomplete, review, wavelet applications in the industrial context are numerous and are present in nearly every domain. However, if one considers only operational devices or software, very few can really be pointed out. Most of them deal with image compression. There are still obstacles in the process of industrialization. Two are principal; one is that the current technology is too popular to be replaced. Such an example is JPEG. Another is the IC design problem. A DCT (2D) needs to take 2K logic gates and 2K RAM inside a chip, but the DWT (2D, too) needs to take 30K logic gates and 100K RAM inside a chip. Presently, one has to admit that the wavelet transform remains essentially a laboratory technique. However, with the development of dedicated IC and efficient software tools, the gap is being closed.[45] Scale discrimination properties of the WT are widely used for practical applications in algorithms of denoising (wavelet shrinkage), scale filtering, fractal analysis, or scalogram visualization. Organizing and concentrating information is also one of the main reasons for the WT's success in numerous applications, particularly in image compression devices. To conclude, we would stress that the wavelet cannot solve all problems and that there are still a lot of limitations inherent to the WT. We recall four of them. DWT, as any decimating algorithm, is not invariant by translation, and this can induce artifacts as well as a lack of consistency in some transient detection algorithms and in signal or image enhancement approaches. The dyadic DWT has a very limited frequency resolution. Sometimes the searched feature is spread on two scales and cannot be clearly detected. The CWT or, in a more interesting way, rational wavelet analysis,[14,17,18] or a frame of overlapping wavelets[139] can overcome this drawback. Transposing a 1D WT to two- (or more) dimensional space is not easy, and the classical separable approach[106] leads to nonisotropic behavior. The horizontal, vertical, and diagonal directions are subject to special attention and can be of interest when processing is linked to the human psychovisual system imitation.[161] On the contrary, when the treatment aims at extracting exact physical information, this anisotropy can be a serious source of errors. Some remedies have been studied; the nonseparable wavelet basis, quincunx analysis,[48] steerable wavelet analysis,[10,49] or geometric wavelets[24,39] are among the best known. Finally, it has been demonstrated that wavelets for an orthogonal basis (in 1D) cannot be symmetrical (zero-phase) if the corresponding filters are of a finite impulse length. For instance, Daubechies, minimum-length wavelets are heavily asymmetric. Signal and images to be treated are most often symmetric and need zero-phase filtering to avoid artifacts. Frequently used as a remedy to this problem, bi-orthogonal wavelets can be of finite length but lead to poor decorrelation between scales. Symlets or Coiflets are not of minimum length, but they provide a quasi-symmetrical analysis function.

## *References*


1. A. Aballe, M. Bethencourt, F. J. Botana, and M. Marcos, "Wavelet transform-based analysis for electrochemical noise," *Electrochem. Commun.* **1**(7), 266 (1999).
2. A. Abbate, "Signal detection and noise suppression using a wavelet transform signal processor: Application to ultrasonic flaw detection," *IEEE Trans. Ultrason. Ferroelectr. Freq. Control* **44**(1), 1–25 (1997).
3. P. Abry, R. Baraniuk, P. Flandrin, R. Riedi, and D. Veitch, "The multiscale nature of network traffic: Discovery, analysis, and modelling," *IEEE Signal Process. Mag.* **19**(3), 28–46 (2002).
4. P. Abry, S. Jaffard, and B. Lashermes, "Revisiting scaling, multifractal, and multiplicative cascades with wavelet leader lens," *Proc. SPIE* **5607**, 103–117 (2004).
5. M. Addis, M. Boniface, S. Goodall, P. Grimwood, S. Kim, P. Lewis, K. Martinez, and A. Stevenson, "Integrated image content and metadata search and retrieval across multiple databases," in *Proc. 2nd Int. Conf. Image Video Retrieval 2003*, pp. 91–100 (2003).
6. T. Aizawa *et al.*, *Electronics Magazine* (Ohmsha Ltd.), pp. 40–41 (Nov. 1995).
7. H. Adeli and A. Karim, *Wavelets in Intelligent Transportation Systems*, John Wiley & Sons, New York (2005).
8. J. M. Aller, T. G. Habetler, R. G. Harley, R. M. Tallam, and S. B. Lee, "Sensorless speed measurement of AC machines using analytic wavelet transform," *IEEE Trans. Ind. Appl.* **38**(5), 1344–1350 (2002).
9. B. K. Alsberg, A. M. Woodward, and D. B. Kell, "An introduction to wavelet transforms for chemometricians: a time-frequency approach," *Chemom. Intell. Lab. Syst.* **37**, 215–239 (1997).
10. J. P. Antoine, R. Murenzi, and P. Vandergheynst, "Directional wavelets revisited: Cauchy wavelets and symmetry detection in patterns,"

*Appl. Comput. Harmon. Anal.* **6**, 314–345 (May 1999).
11. M. Antonini, M. Barlaud, P. Mathieu, and I. Daubechies, "Image coding using the wavelet transform," *IEEE Trans. Image Process.* **2**(2), 205–220 (1992).
12. J. A. Antonino-Daviu, M. Riera-Guasp, J. R. Folch, and M. P. M. Palomares, "Validation of a new method for the diagnosis of rotor bar failures via wavelet transform in industrial induction machines," *IEEE Trans. Ind. Appl.* **42**(4), 990–996 (2006).
13. A. Arneodo, "Wavelet analysis of fractals," in *Wavelets, Theory and Applications*, Erlebacher *et al.* (Eds.), Oxford Press, Oxford (1996).
14. P. Auscher, "Wavelet bases for $L^2(R)$ with rational dilation factor," in *Wavelets and Their Applications*, M. B. Ruskai *et al.* (Eds.), pp. 439–452, Jones and Bartlett, Boston (1992).
15. V. Barat *et al.*, "Wavelet analysis of MFL signal for steel wire rope testing," in *Proc. 15th World Congress NDT* (2000).
16. W. Batko and A. Mikulski, "Application of wavelet methods to magnetic testing of steel ropes," in *Proc. Int. Carpathian Control Conf. ICCC' 2002*, pp. 33–38 (2002).
17. A. Baussard, F. Nicolier, and F. Truchetet, "Rational multiresolution analysis and fast wavelet transform: Application to wavelet shrinkage denoising," *Signal Process.* **84**, 1735–1747 (2004).
18. I. Bayram and I. W. Selesnick, "Design of orthonormal and overcomplete wavelet transforms based on rational sampling factors," *Proc. SPIE* **6763** (2007).
19. P. T. Bourgeat, F. Mériaudeau, P. Gorria, and K. W. Tobin, "Gabor filters applied to pattern wafers segmentation," *Proc. SPIE* **5607**, 148–155 (2004).
20. J. N. Bradley, C. M. Brislawn, and T. Hopper, "The FBI wavelet/scalar quantization standard for gray-scale fingerprint image compression," *Proc. SPIE* **1961**, 293–304 (1993).
21. H. Briesen and W. Marquardt, "An adaptive multigrid method for steady-state simulation of petroleum mixture separation processes," *Ind. Eng. Chem. Res.* **42**, 2334–2348 (2003).
22. C. M. Brislawn, "Fingerprints go digital," *Notices AMS* **42**(11), 1278–1283 (1995).
23. S. Bukkapatnam, S. Kumara, A. Lakhtakia, and P. Srinivasan, "Neighborhood method and its coupling with wavelet method for nonlinear signal separation of contaminated chaotic time-series data," *Signal Process.* **82**, 1351–1374 (2002).
24. E. J. Candès, "Ridgelets: Theory and applications," Ph.D. thesis, Stanford University (1998).
25. P. Carré and D. Helbert, "Ridgelet decomposition: Discrete implementation and color denoising," *Proc. SPIE* **6001** (2005).
26. C. D. Cernea, I. A. Salomie, A. Alecu, P. Schelkens, and A. Munteanu, "Wavelet-based scalable L-infinity-oriented coding of MPEG-4 MESHGRID surface models," *Proc. SPIE* **6001** (2005).
27. H. Y. Chan, C. Raju, H. Sarri-Sarraf, and E. F. Hequet, "A general approach to defect detection in textured materials using a wavelet domain model and level set," *Proc. SPIE* **6001** (2005).
28. R. S. Chang, J. Y. Sheu, and C. H. Lin, "New image fusion method applied in two wavelength detection of biochip spot," *Proc. SPIE* **4556**, 45–53 (2001).
29. R. S. Chang, J. Y. Sheu, and C. H. Lin, "Analysis of Seidel aberration by use of the discrete wavelet transform," *Appl. Opt.* **41**(13), 2408–2413 (May 2002).
30. R. S. Chang, J. Y. Sheu, C. H. Lin, and H. C. Liu, "Analysis of CCD moiré pattern for micro-range measurements using the wavelet transform," *Opt. Laser Technol.* **35**(1), 43–47 (2003).
31. P. Cheng, J. Li, and C.-C. J. Kuo, "Rate control for an embedded wavelet video coder," *IEEE Trans. Circuits Syst. Video Technol.* **7**(4), 696–702 (1997).
32. B. Cipra, "Wavelet applications come to the fore," *SIAM News* **26**(7), (1993).
33. V. Colla, M. Sgarbi, and L. M. Reyneri, "Neur–wavelet parametric modeling," *Int. Joint. Conf. on Neural Networks* **4**, 499–504 (2000).
34. V. Colla, L. M. Reyneri, and M. Sgarbi, "Parametric characterization of hardness profiles of steels with neuro–wavelet networks," *Int. Work-Conf. on Artificial and Natural Neural Networks* **2**, 606–614 (1999).
35. C. Combastel, S. Lesecq, S. Petropol, and S. Gentil, "Model-based and wavelet approaches for induction drive on-line fault detection," *Control Eng. Pract.* **10**, 493–509 (2002).
36. D. Cornforth, R. Middleton, and J. Tusek, "Visualisation of electrical transient using the wavelet transform," in *Proc. AISTA 2000* (2000).
37. I. Daubechies, *Ten Lectures on Wavelets*, SIAM, CBMS-NSF, Philadelphia (1992).
38. R. A. DeVore, B. Jawerth, and B. J. Lucier, "Image compression through wavelet transform coding," *IEEE Trans. Inf. Theory* **38**(2), 719–746 (1992).
39. M. N. Do and M. Vetterli, "The finite ridgelet transform for image representation," *IEEE Trans. Image Process.* **12**(1), 16–28 (2003).
40. D. Donoho, "De-noising by soft-thresholding," *IEEE Trans. Inf. Theory* **12**(1), 151–160 (1995).
41. D. L. Donoho and M. R. Duncan, "Digital curvelet transform for image denoising," *Proc. SPIE* **4056**, 12–29 (2000).
42. H. Eeckaut, M. Christiaens, H. Devos, and D. Stroobandt, "Implementing a hardware-friendly wavelet entropy codec for scalable video," *Proc. SPIE* **6001** (2005).
43. A. Erramilli, O. Narayan, A. Neidhardt, and I. Saniee, "Performance impacts of multiscaling in wide area TCP/IP traffic," in *Proc. IEEE* (2000).
44. Y. Fan and B. Whitcher, "A wavelet solution to the spurious regression of fractionally differenced processes," *Appl. Stochastic Models in Business and Industry* **19**, 171–183 (2003).
45. H. C. Fang, Y. W. Chang, C. C. Cheng, and L. G. Chen, "Memory efficient JPEG 2000 architecture with stripe pipeline scheduling," *IEEE Trans. Signal Process.* **54**(12), 4807–4816 (2006).
46. H. Farid and S. Lyu, "Higher-order wavelet statistics and their application to digital forensics," in *Proc. IEEE Workshop on Statistical Analysis in Computer Vision* (2003).
47. N. Farvardin, H. Jafarkhani, J. Johnson, and R. Bhattacharya, "Real-time wavelet-based video compression system using multiple TMS320C40s," application report from Texas Instruments (1997).
48. J. C. Feauveau, "Analysis multirésolution avec un facteur de résolution $\sqrt{2}$," *J. de Traitement du Signal* **7**(2), 117–128 (1990).
49. W. T. Freeman and E. H. Adelson, "The design and use of steerable filters," *IEEE Trans. Pattern Anal. Mach. Intell.* **13**(9), 891–906 (1991).
50. D. Gabor, *J. Inst. Electr. Eng.* **93**, 429 (1946).
51. R. Gao, E. Eryurek, and L. H. Tsoukalas, "A novel neural-wavelet diagnostics approach: Application to magnetic flowmeter," *Int. J. Artif. Intelli. Tools* **10**(3), 421–429 (2001).
52. A. M. Gaouda, M. M. A. Salama, M. R. Sultan, and A. Y. Chikhani, "Power quality detection and classification using wavelet-multiresolution signal decomposition," *IEEE Proc. Power Delivery* **14**(4), 1469–1476 (1999).
53. R. Gencay, F. Selcuk, and B. Whitcher, "Systematic risk and time scales," *Quant. Finance* **3**(2), 108–116 (2003).
54. L. Ghouti, A. Bouridane, M. K. Ibrahim, and S. Boussakta, "Digital image watermarking using balanced multiwavelets," *IEEE Trans. Signal Process.* **54**(4), 1519–1536 (2006).
55. R. Gomez-Sanchez and D. Andina, "Wavelet neural network for detection of signals in communication," *Proc. SPIE* **3391**, 265–274 (1998).
56. W. Gong, T. Obikawa, and T. Shirakashi, "Monitoring of tool wear states in turning based on wavelet analysis," *JSME Int. J., Ser. I* **40**(3), 447–453 (1997).
57. A. Grossman and J. Morlet, "Decomposition of Hardy functions into square integrable wavelets of constant shape," *SIAM J. Math. Anal.* **15**, 723–736 (1984).
58. T. Gulzow, A. Engelsberg, and U. Heute, "Comparison of a discrete wavelet transformation and nonuniform polyphase filterbank applied to spectral-subtraction speech enhancement," *Signal Process.* **64**, 5–19 (1998).
59. I. Guskov, W. Sweldens, and P. Schröder, "Multiresolution signal processing for meshes," in *Proc. ACM SIGGRAPH*, pp. 325–334 (1999).
60. H. Hoppe, "Progressive meshes," in *Proc. ACM SIGGRAPH*, pp. 99–108 (1996).
61. D. E. Halstead and D. Wisler, "Boundary layer development in axial compressor and turbines," *ASME papers*, pp. 461–464 (1995).
62. G. Harrison, I. Koren, M. P. Lewis, and F. J. Taylor, "Application of wavelet and Wigner analysis to gas turbine vibration signal processing," *Proc. SPIE* **3391**, 490–501 (1998).
63. H. Hatanaka and T. Arakawa, "Ultrasonic examination of thermal sprayed coatings with frequency analysis," in *Proc. 15th World Conf. Nondestructive Testing* (2000).
64. Z. Hu, Y. Chen, and S. Islam, "Multiscaling properties of soil moisture images and decomposition of large and small scale features using wavelet transforms," *Int. J. Remote Sens.* **19**, 2451–2467 (1998).
65. H. Yan, "Fibre flocks in the suspension," Forest Products Industry Research College (Sweden), http://www.fpirc.kth.se/Associate/Huawei_Yan.html (2004).
66. H. Yan, "Fibre suspension flocculation under simulated forming conditions," Ph.D. thesis, Forest Product Industry Research College in KTH, Stockolm (2004).
67. H. Y. Chan, H. Sari-Sarraf, B. I. Grinstead, and S. S. Gleason, "Content-based compression of mammograms with fractal-based segmentation and a modified JPEG2000," *Opt. Eng.*, **43**(12), 2986–2993 (2004).
68. F. Idris and S. Panchanathan, "Image indexing using wavelet vector quantization," *Proc. SPIE* **2606**, 269–275 (1995).
69. H. Inoue, "Experimental wavelet analysis of flexural waves in beams," *Exp. Mech.* **36**(3), 212–217 (1996).
70. H. Inoue *et al.*, "Determination of ultrasonic velocity and attenuation by wavelet analysis of echo waveform," *J. Jap. Soc. for Non-Destructive Inspection* **46**(3), 206–213 (1997).
71. IO Industries, "Video savant features: Uncompressed or wavelet compressed recording," http://www.ioindustries.com/videosavant/wavelet.html.





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72. C. E. Jacobs, A. Finkelstein, and D. H. Salesin, "Fast multiresolution image querying," in *Proc. SIGGRAPH95* (1995).
73. W. Jasper, S. Garnier, and H. Potlapalli, "Texture characterization and defect detection using adaptive wavelets," *Opt. Eng.* **35**(11), 3140–3149 (1996).
74. T. J. Johnson and D. E. Adams, "Rolling tire diagnostic experiments for identifying incipient bead damage using time, frequency and phase plane analysis," *Society of Automotive Engineers' 2006 World Congress* (2006).
75. K. J. Jones, "3D wavelet image processing for spatial and spectral resolution of Landsat images," *Proc. SPIE* **3391**, 218–225 (1998).
76. K. J. Jones, "Wavelet image processing: Assessment of spatial and spectral resolution of Landsat images," *Proc. SPIE* **4056**, 137–147 (2000).
77. A. Kaarna and J. Parkkinen, "Multiwavelets in spectral image compression," *Proc. 11th SCIA*, pp. 327–334 (1999).
78. G. Kaiser, "Wavelet electrodynamics," in *Progress in Wavelet Analysis and Applications*, Y. Meyer and S. Roques (Eds.), pp. 729–734, Editions Frontiers, Paris, (1993).
79. S. V. Kamarthi, S. R. Kumara, and P. H. Cohen, "Flank wear estimation in turning through wavelet representation of acoustic emission signals," *J. Manuf. Sci. Eng.* **122**, 12–19 (2000).
80. P. Kang and D. Birtwhistle, "Condition assessment of power transformer on-load tap-changers using wavelet analysis and self-organizing map-field evaluation," *IEEE Trans. Power Deliv.* **18**(1), 653–656 (2003).
81. D. A. Karras, S. A. Karkanis, D. Iakovidis, D. E. Maroulis, and B. G. Mertzios, "Support vector machines for improved defect detection in manufacturing using novel multidimensional wavelet feature extraction involving vector quantization and PCA techniques," in *Proc. NIMIA-SC2001* (2001).
82. A. Kareem and T. Kijewski, "Time-frequency analysis of wind effects on structures," *J. Wind. Eng. Ind. Aerodyn.* **90**, 1435–1452 (2002).
83. K. Karibasappa and S. Patnaik, "Face recognition by ANN using wavelet transform coefficients," *Inst. of Eng. (India) J: Comp. Eng. Div.* **85**, 17–23 (2004).
84. N. Kawagashira, Y. Ohtomo, K. Murakami, K. Matsubara, J. Kawai, P. Carninci, Y. Hayashizaki, and S. Kikuchi, "Wavelet profiles: Their application in *Oryza sativa* DNA sequence analysis," in *IEEE Comp. Soc. Bioinformatics Conf. (CSB'02)* (2002).
85. H. Kikuchi, M. Nakashizuka, H. Watanabe, and N. Tomisawa, "Fast wavelet transform and its application to detecting detonation," *IEICE Trans. Fundamentals* **E-75-A**, 980–987 (1992).
86. M. Kobayashi, "Listening for defect: Wavelet-based acoustical signal processing in Japan," *SIAM News* **29**(2), 24 (1996).
87. O. Kocsis, L. Costaridou, L. Varaki, E. Likaki, C. Kalogeropoulou, and G. Panayiotakis, "Evaluating wavelet compression in microcalcification in mammography," in *Proc. 14th Int. Conference on Digital Signal Processing*, 2, pp. 535–538 (2002).
88. A. Krishnan, K. B. Li, and P. Issac, "Rapid detection of conserved regions in protein sequences using wavelets," *Silico Bio.* **4**, 0013 (2004).
89. P. Kumar and E. Foufoula-Georgiou, "Wavelet analysis for geophysical applications," *Rev. Geophys.* **35**, 385–412 (1997).
90. J. H. Kurz, H. J. Ruck, F. Flinck, and C. U. Grosse, "Wavelet algorithms for non destructive testing," in *Proc. Non-destructive Testing in Civil Engineering 2003*, (2003).
91. O. Laligant, F. Truchetet, and E. Fauvet, "Wavelets transform in artificial vision inspection of threading," in *Proc. IECON'93*, pp. 513–518 (1993).
92. B. Y. Lee and Y. S. Tarng, "Application of the discrete wavelet transform to the monitoring of tool failure in end milling using the spindle motor current," *Int. J. Adv. Manuf. Technol.* **15**, 238–243 (1999).
93. C. S. Lee *et al.*, "Feature extraction algorithm based on adaptive wavelet packet for surface defect classification," in *Proc. ICIP 96* (1996).
94. S. Lesecq, S. Taleb, and S. Gentil, "Fault detection based on wavelet transform and fuzzy decision making," in *Proc. ACD'05* (2005).
95. J. Lewalle and D. E. Ashpis, "Demonstration of wavelet techniques in the spectral analysis of bypass transition data," NASA technical report TP-3555 (1995).
96. J. Lewalle, "Analysis of web defects by correlating 1-D Morlet and 2-D Mexican hat wavelet transforms," *Proc. SPIE* **6001** (2005).
97. N. X. Lian, V. Zagorodnov, and Y. P. Tan, "Error inhomogeneity in wavelet-based compression," *IEEE Trans. Signal Process.* **55**(7), 3659–3669 (2007).
98. H. Li, H. Hu, T. Kobayashi, T. Saga, and N. Taniguchi, "Wavelet multi-resolution analysis of dual-plane stereoscopic PIV measurement results in a lobed jet," in *Proc. 4th Int. Symp. Particle Image Velocimetry* (2001).
99. J. Li and S. Lei, "An embedded still image coder with rate-distortion optimization," *IEEE Trans. Image Process.* **8**(7), 913–924 (1999).
100. A. R. Lindsey and J. C. Dill, "Digital transceiver implementation for wavelet packet modulation," *Proc. SPIE* **3391**, 255–264 (1998).
101. J. Liu, P. Pillay, and H. Douglas, "Wavelet modeling of motor drives applied to the calculation of motor terminal overvoltages," *IEEE Trans. Ind. Electron.* **51**(1), 61–66 (2004).
102. J. Liu, P. Pillay, and P. Ribeiro, "Wavelet analysis of power system transients using scalograms and multiresolution analysis," *Electr. Mach. Power Syst. J.* **27**(12), 1331–1342 (1999).
103. F. Lumbreras, J. Serrat, R. Baldrich, M. Vandrell, and J. J. Villanueva, "Color texture recognition through multiresolution features," in *Proc. Int. Conf. Quality Control Artif. Vis.*, 1, 114–121, Cépaduès Ed. (2001).
104. S. Maquiné de Souza, Y. Grandvalet, and T. Denoeux, "Monitoring of sludge dewatering equipment by image classification," *Proc. SPIE* **5607**, 34–45 (2004).
105. S. Mallat, "A theory for multiresolution signal decomposition; the wavelet representation," *IEEE Trans. Pattern Anal. Mach. Intell.* **11**(7), 674–693 (1989).
106. S. Mallat, *A Wavelet Tour of Signal Processing*, Academic Press, London (1999).
107. D. Mahmoudi and A. Drygajlo, "Combined Wiener and coherence filtering in wavelet domain for microphone array speech enhancement," in *Proc. ICASSP*, pp. 385–388 (1998).
108. M. K. Mandal, T. Aboulnasr, and S. Panchanathan, "Illumination invariant image indexing using moments and wavelets," *J. Electron. Imaging* **7**(2), 282–293 (1998).
109. M. W. Marcellin, M. Gormish, A. Bilgin, and M. P. Boliek, "An overview of JPEG2000," in *Proc. Data Compression Conf.*, pp. 523–544 (2000).
110. Y. Meyer, *Ondelettes et Opérateurs I: Ondelettes*, Hermann, Paris, (1990).
111. A. Mikulski, "Application of the wavelet analysis to mine gear rope diagnostic testing processes," Ph.D. thesis, Academy of Mining and Metallurgy, Kracow (2001).
112. M. S. Kim, T. Kim, Y.-J. Shin, S. S. Lam, and E. J. Powers, "A wavelet-based approach to detect shared congestion," in *Proc. ACM SIGCOMM 2004* (2004).
113. M. P. Mitrea, T. B. Zaharia, F. J. Prêteux, and A. Vlad, "Video watermarking based on spread spectrum and wavelet decomposition," *Proc. SPIE* **5607**, 156–164 (2004).
114. M. Morehart, F. Murtagh, and J. L. Starck, "Multiresolution spatial analysis," in *Proc. Geo Computation* (1999).
115. K. Mori, N. Kasashima, J. C. Fu, and K. Muto, "Prediction of small drill bit breakage by wavelet transforms and linear discriminant functions," *Int. J. Mach. Tools Manuf.* **39**, 1471–1484 (1999).
116. J. Morlet, G. Arens, E. Fourgeau, and D. Giard, "Wave propagation and sampling theory 1, complex signal and scattering in multilayered media," *Geophysics* **47**, 203–221 (1982).
117. K. Morley, "Imagery explosion drives technology beyond compression," *Geoworld* (Sept. 2002).
118. P. Moyo and J. M. W. Brownjohn, "Detection of anomalus structural behaviour using wavelet analysis," *Mech. Syst. Signal Process.* **16**(2–3), 429–445 (2002).
119. N. Munehiro and I. Yoshihisa, "Wavelet transform domain blind deconvolution," *Signal Process.* **68**(1), 119–124 (1998).
120. G. P. Nason and T. Sapatinas, "Wavelet packet transfer function modelling of nonstationary time series," *Stat. Comput.* **12**(1), 45–56 (2002).
121. S. G. Nikolov, H. Hutter, and M. Grasserbauer, "De-noising of SIMS images via wavelet shrinkage," *Chemom. Intell. Lab. Syst.* **34**, 263–273 (1996).
122. A. C. Okafor and A. Dutta, "Structural damage detection in beams by wavelet transforms," *Smart Mater. Struct.* **9**(6), 906–917 (2000).
123. H. Okamoto, T. Murata, T. Kataoka, and S. I. Hata, "Plant classification for weed detection using hyperspectral imaging with wavelet analysis," *Weed Biol. Manage.* **7**, 31–37 (2007).
124. C. A. Paget, S. Grondel, K. Levin, and C. Delebarre, "Damage assessment in composites by Lamb waves and wavelet coefficients," *Smart Mater. Struct.* **12**, 393–402 (2003).
125. S. Parvez and Z. Gao, "A novel controller based on multiresolution decomposition using wavelet transform," in *Proc. Instrument. Syst. Automation 2002* (2002).
126. S. Parvez and Z. Gao, "A wavelet-based multiresolution PID controller," *IEEE Trans. Ind. Appl.* **41**(2), 537–543 (2005).
127. D. Percival and A. Walden, *Wavelet Methods for Time Series Analysis*, Cambridge University Press, Cambridge (2002).
128. Z. K. Peng and F. L. Chu, "Application of the wavelet transform in machine condition monitoring and fault diagnostics: A review with bibliography," *Mech. Syst. Signal Process.* **18**(2), 199–221 (2004).
129. J. Ramirez-Nino, S. Rivera-Castaneda, V. R. Garcia-Colon, and V. M. Castano, "Analysis of partial discharges in insulating materials through the wavelet transform," *Comput. Mater. Sci.* **9**, 379–388 (1998).
130. R. H. Riedi, M. S. Crouse, V. Ribeiro, and R. G. Baraniuk, "A multifractal wavelet model with application to network traffic," *IEEE Trans. Inf. Theory* **45**(3), 992–1018 (1999).
131. D. C. Robertson, O. I. Camps, J. S. Mayer, and W. B. Gish, "Wavelets and electromagnetic power systems transients," *IEEE Trans. Power Deliv.* **11**(2), 1050–1058 (1996).

132. J. Rombaut, A. Pizurica, and W. Philips, "Passive error concealment for wavelet coded images adapted to a directional image correlation," *Proc. SPIE* **6001** (2005).
133. A. Roueff, J. Chanussot, and J. Mars, "Use of time-scale representations for the analysis of seismic signals," *Proc. SPIE* **5266**, 226–237 (2004).
134. E. A. Rying, "A novel focused local learning wavelet network with application to in situ monitoring during selective silicon epitaxy," Ph.D. thesis, North Carolina State University (2004).
135. S. Santoso, E. J. Power, W. M. Grady, and P. Hofmann, "Power quality assessment via wavelet transform analysis," *IEEE Trans. Power Deliv.* **11**(2), 924–930 (1996).
136. H. Sari-Sarraf and J. Goddard, "Vision system for on-loom fabric inspection," *IEEE Trans. Neural Netw.* **36**(6), 1252–1259 (1999).
137. S. Sarvotham, R. Riedi, and R. Baraniuk, "Connection-level analysis and modeling of network traffic," in *ACM SIGCOMM Internet Measurement Workshop* (2001).
138. T. Schrötter and K. Lieven, "Application of the process analyzer in chemical industry," in *Proc. TCA Workshop on Applications in Chemical and Biochemical Industries* (1999).
139. I. W. Selesnick, "Higher density discrete wavelet transform," *IEEE Trans. Signal Process.* **54**(8), 3039–3048 (2006).
140. J. W. Seok and K. S. Bae, "Speech enhancement with reduction of noise components in the wavelet domain," in *Proc. ICASSP*, pp. 1223–1326 (1997).
141. A. Serdaroglu, A. Ertuzun, and A. Ercil, "Defect detection in textile fabric images using wavelet transforms and independent component analysis," *Patt. Recog. Image Anal.* **16**(1), 61–64 (2006).
142. J. Shapiro, "Embedded image coding using zerotree of wavelet coefficients," *IEEE Trans. Signal Process.* **41**, 3445–3462 (1993).
143. J. Y. Sheu, R. S. Chang, C. H. Lin, and P. L. Fan, "Analysis of wave aberration by use of the wavelet transform," *Chin. J. Phys. (Taipei)* **40**(1), 20–30 (2002).
144. J. Y. Sheu, R. S. Chang, and C. H. Lin, "Analysis of primary aberration with the two-dimension discrete wavelet transform," *Proc. SPIE* **4056**, 372–378 (2000).
145. J. Y. Sheu, C. H. Lin, and R. S. Chang, "Analysis of 3rd order spherical aberration with the continuous wavelet transform," *Proc. SPIE* **4056**, 507–514 (2000).
146. T. Shirakawa, A. Kawamura, and T. Nakatsuji, "Application of the second generation wavelet transform for pavement preventive maintenance," *J. Eastern Asia Soci. Transportation Studies* **6**, 1113–1122 (2005).
147. M. Solanki, Y. H. Song, S. Potts, and A. Perks, "Transient protection of transmission line using wavelet transform," in *Proc. 7th Int. Conf. Developments in Power System Protection*, pp. 299–302 (2001).
148. J. L. Stark and A. Bijaoui, "Filtering and deconvolution by the wavelet transform," *Signal Process.* **35**, 195–211 (1994).
149. G. Stephanopoulos, O. Karsligil, and M. Dyer, "Multiscale aspects in model-predictive control," *J. Process Control* **10**, 275–282 (2000).
150. J. Suh, S. Kumara, and S. Mysore, "Machinery fault diagnosis and prognosis: Applications of advanced signal processing techniques," *CIRP Ann.* **48**, 317–324 (2000).
151. H. Sun, H. Xiao, F. Yang, B. Ran, Y. Tao, and Y. Oh, "Wavelet preprocessing for local linear traffic prediction," in *Proc. TRB 2004 Annual Meeting* (2004).
152. W. Sweldens, "The lifting scheme: A construction of second generation wavelets," Technical report 6, Industrial Mathematics Initiative, Dept. of Mathematics, University of South Carolina (1995).
153. D. C. Tat Wai and X. Yibin, "A novel technique for high impedance fault identification," *IEEE Trans. Power Deliv.* **13**(3), 738–744 (1998).
154. D. Taubman and A. Zakhor, "A common framework for rate and distortion based scaling of highly scalable compressed video," *IEEE Trans. Circuits Syst. Video Technol.* **6**(4) (1996).
155. D. Taubman, "High performance scalable image compression with EBCOT," *IEEE Trans. Image Process.* **9**(7), 1158–1170 (2000).
156. D. S. Taubman and M. W. Marcellin, *JPEG 2000: Image Compression Fundamentals, Standards and Practice*, Kluwer, New York (2003).
157. J. Tham, S. Ranganath, and A. Kassim, "Highly scalable wavelet-based video codec for very low bit-rate environment," *IEEE J. Sel. Areas Commun.* (1996).
158. L. Tian, J. F. Reid, and J. W. Hummel, "Development of a precision sprayer for site-specific weed management," *Trans. ASAE* **42**(4), 893–900 (2000).
159. F. Truchetet, *Ondelettes pour le Signal Numérique*, Hermes, Paris (1998).
160. F. Truchetet, (Ed.), *Wavelet Applications in Industrial Processing*, *Proc. SPIE* 5266 (2004).
161. F. Truchetet, B. Joanne, F. Pérot, and O. Laligant, "High quality still color image compression," *Opt. Eng.* **39**(2), 409–414 (2000).
162. F. Truchetet and O. Laligant (Eds.), *Wavelet Applications in Industrial Processing IV*, *Proc. SPIE* 6383 (2006).
163. F. Truchetet and O. Laligant, "Wavelets in industrial application: A review," *Proc. SPIE* **5607**, (2004).
164. M. C. Tsao, "Application of wavelet-probabilistic network to power quality and characteristic harmonics detection," Ph.D. thesis, NSYSU, Taiwan (2004).
165. R. W. Tucker, S. W. Kercel, and V. K. Varma, "Characterization of gas pipeline flaws using wavelet analysis," *Proc. SPIE* **5132**, 485–493 (2003).
166. M. Unser and T. Blu, "Wavelet theory demystified," *IEEE Trans. Signal Process.* **51**(2), 470–483 (2003).
167. M. Unser, "Mathematical properties of the JPEG2000 wavelet filters," *IEEE Trans. Image Process.* **12**(9), 1080–1090 (2003).
168. M. Unser, "Texture classification and segmentation using wavelet frames," *IEEE Trans. Image Process.* **4**(11), 1549–1560 (1995).
169. P. Vandergheynst, M. Kutter, and S. Winkler, "Wavelet-based contrast computation and application to digital image watermarking," *Proc. SPIE* **4119**, 82–92 (2000).
170. M. Vetterli and J. Kovacevic, *Wavelets and Subband Coding*, Prentice Hall, Englewood Cliffs, NJ (1995).
171. J. B. Vioix, J. P. Douzals, and F. Truchetet, "Development of a multispectral imagery device devoted to weed detection," *J. Electron. Imaging* **13**(3), 547–552 (2004).
172. G. Wang, "Four-bank compactly supported bisymmetric orthonormal wavelets bases," *Opt. Eng.* **43**(10), 2362–2368 (2004).
173. W. J. Wang, "Wavelets for detecting mechanical faults with high sensitivity," *Mech. Syst. Signal Process.* **15**(4), 685–696 (2001).
174. W. J. Wang and P. D. McFadden, "Application of wavelets to gearbox vibration signals for fault detection," *J. Sound Vib.* **192**, 927–939 (2001).
175. L. Wang, M. G. Mehrabi, and E. Kannatey-Asibu, "Tool wear monitoring in reconfigurable machining systems through wavelet analysis," *J. Electron. Imaging* (1998).
176. J. Wang, G. Wiederhold, and O. Firschein, "System for screening objectionable images using Daubechies wavelets and color histograms," in *Proc. 4th int. conf. Interactive Distrib. Multimedia Syst. Telecommuni. Services (IDMS'97)*, Springer-Verlag LNCS 1309, 20–30 (1997).
177. M. Wang and M. van der Schaar, "Operational rate-distortion modeling for wavelet video coders," *IEEE Trans. Signal Process.* **54**(9), 3505–3517 (2006).
178. X. H. Wang, R. S. H. Istepanian, and Y. H. Song, "Microarray image enhancement by denoising using stationary wavelet transform," *IEEE Trans. Nanobiosci.* **2**(4) 184–189 (2003).
179. Z. Wang and A. Bovik, "A universal image quality index," *IEEE Trans. Signal Process.* **9**, 81–84 (2002).
180. R. M. West and R. A. Williams, "Opportunities for data fusion in multi-modality tomography," in *Proc. 1st World Congress on Industrial Process Tomography* (1999).
181. R. L. Westra, "Adaptive control using CCD-images: Toward a template-invariant approach," in *Proc. 7th Conf. Intelli. Learning* (2000).
182. R. L. Westra, J. M. Shippen, and N. D. Freear, "Printing quality control using template independent neurofuzzy classification," in *Proc. 7th Eur. Conf. Intell. Tech. Soft Computing* (1999).
183. M. Wolkenstein, H. Hutter, S. G. Nikolov, and M. Grasserbauer, "Improvement of SIMS image classification by means of wavelet de-noising," *J. Anal. Chem. USSR* **357**(7), 783–788 (1997).
184. Y. Wu, P. Escande, and R. Du, "A new method for real-time tool condition monitoring in transfer machining stations," *J. Manuf. Sci. Eng.* **123**, 339–347 (May 2001).
185. R. S. Wu, X. L. Dong, and J. H. Gao, "Application of acoustic wavelet transform to seismic data processing," expanded abstract of the technical program from SEG, 68th annual meeting (1998).
186. C. Xiangxun, "Wavelet-based detection localization, quantification and classification of short duration power quality disturbances," in *Proc. IEEE Power Eng. Soc. Winter Meeting 2002* 2, 931–936 (2002).
187. X. Z. Yang, G. Pang, and N. Yung, "Discriminative fabric defect detection using adaptive wavelets," *Opt. Eng.* **41**(12), 3116–3126 (2002).
188. L. Yang, H. Fong, and Y. Wong, "The application of wavelet transform in magnetic flux leakage test of pipeline,"*Proc. 10th APCNDT* (2001).
189. C. C. Yang, S. H. Kwok, and M. Yip, "Image browsing for infomediaries," in *Proc. 35th Hawaii Int. Conf. System Sci.* (2002).
190. X. Yibin, D. C. Tat Wai, and W. W. L. Keerthipala, "A new technique using wavelet analysis for fault location," in *Proc. IEE Conf. Develop. Power System Protection*, 434, 231–234 (1997).
191. X. Yin, G. Wu, and S. Qu, "Application of wavelet transform in 3D seismic sequence analysis," expanded abstract of the technical program from SEG, 68th annual meeting (1998).
192. H. Yu, B. Wu, and L. Chen, "On-line technology of check and measure of oil and gas pipeline by magnetic flux leakage," *Practical Measuring and Testing Tech.*, **5**, 1–9 (1997).
193. W. G. Zanardelli, E. G. Strangas, and S. Aviyente,"Identification of intermittent electrical and mechanical faults in permanent-magnet

AC drives based on time-frequency analysis," *IEEE Trans. Ind. Appl.* **43**(4), 971–980 (2007).

194. A. Zandi, J. D. Allen, E. L. Schwartz, and M. Boliek, "CREW: Compression with reversible embedded wavelets," in *Proc. IEEE Conf. Data Compression*, pp. 212–221 (1995).
195. A. Zatsman, M. Rossman, R. Greene, W. Hooper, P. Halmark, and D. Skolnick, "Industry's first integrated wavelet video codec sets new standards for cost, integration and flexibility," Analog Devices technical report, http://www.analog.com/library/analogDialogue/archives/30-2/wavelet.html (2004).
196. Q. Zhang and A. Benveniste, "Wavelet networks," *IEEE Trans. Neural Netw.* **3**(6), 889–898 (1992).
197. W. Zhu and M. Barth, "Vehicle trajectory-based road type and congestion recognition using wavelet analysis," in *Proc. IEEE ITSC 2006*, pp. 879–884 (2006).

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