Paper machine data analysis and compression using wavelets

ZORAN NESIC, MICHAEL DAVIES, AND GUY DUMONT

ABSTRACT

This paper describes the analysis of paper machine process data using discrete wavelet transforms. The techniques have been adapted from a general signal analysis theory that has been developed in recent years. It is shown that wavelets are an effective representation for the detection of basis weight and moisture process variations in noisy data and lead to improved estimation and visualization of the machine-direction and cross-direction variations. Using simulated data, it has been shown that the new methods produce results superior to conventional industrially accepted procedures. Industrial data also have been analyzed, and it is apparent that the method has many desirable characteristics.

The second main advantage of the method has been to allow significant compression of the process data without diminishing the ability to reconstruct accurate and detailed profiles. It has been shown that the compression method can be embedded into the estimation algorithm, producing excellent results without major expense in computation time. The ability to reduce data storage requirements is of importance in mill-wide process-monitoring systems.

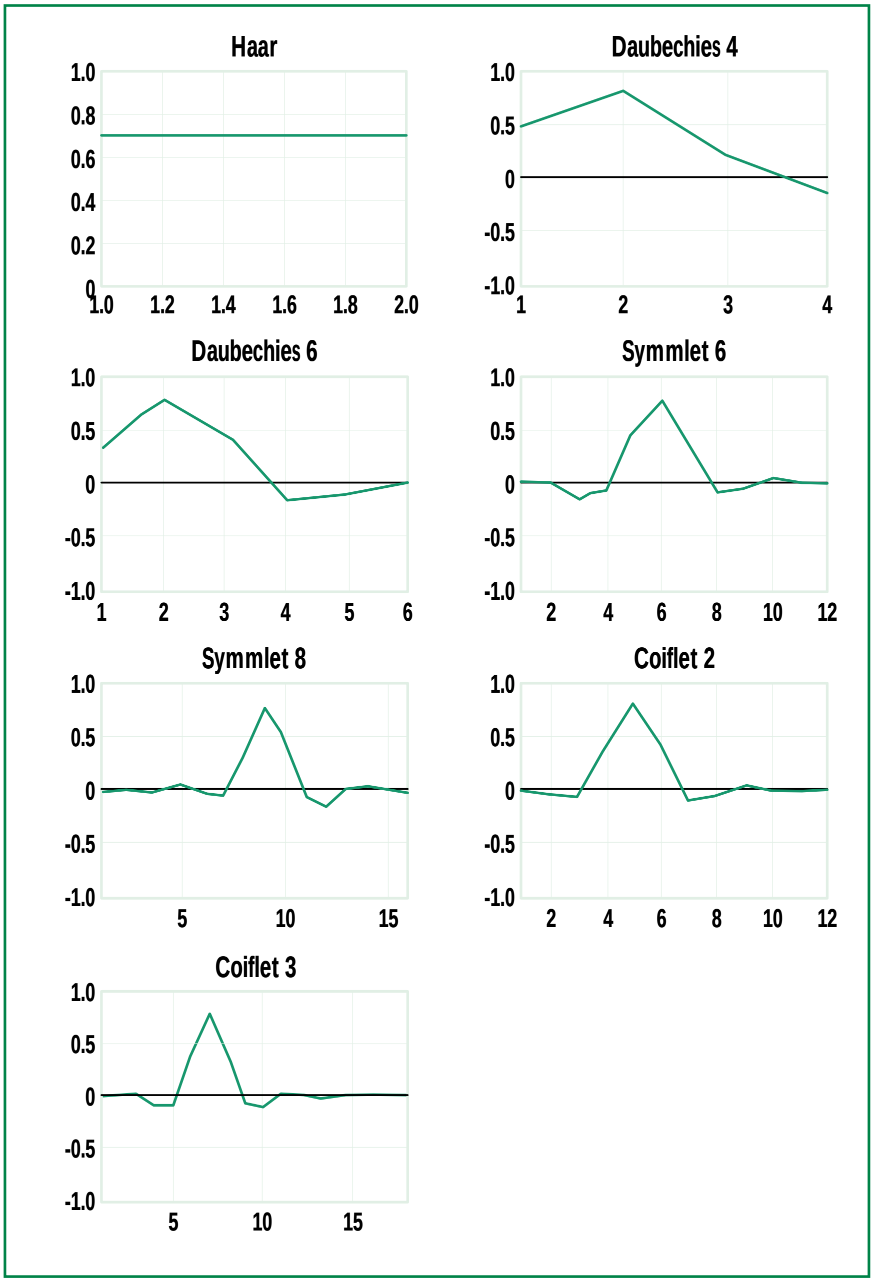
Application:

Wavelet representation is used to identify profile irregularities that might otherwise not be detected and to separate out components that should be eliminated by an effective CD controller, taking into account the actuator spacing. The method can also be used to provide superior on-line operator displays of sheet basis weight and moisture process data.

THE CONTROL OF BASIS WEIGHT and moisture on a paper machine depends on data gathered from scanning sensors that traverse the sheet (in the cross direction—CD), taking up to 3000 measurements over a period of about 20 seconds. Since the speed of the paper sheet may be up to 25 m/s—more than 100 times the sensor speed—the combination of the paper trajectory (in the machine director—MD) and the sensor movement (in the CD) produces a zigzag pattern of measurements. The measured sequence of values thus contains information about both MD and CD variations. Separating this nonuniformly spaced set of samples into MD and CD components represents a major problem in estimation and control. The MD process variations are considered to be time dependent, fast and independent of the CD position. Control action in the MD is normally taken at least once every scan. Changes in CD profiles are considered to be relatively slow, and CD control action is often taken only every 2–4 scans *(1, 2)*. Faster detection of MD upsets is increasingly desirable with changes in paper machine design.

Most industrial estimators are based on the exponential multiple scan trending (EXPO) algorithm *(3)*. Assuming slowly changing zero-mean CD profiles, this algorithm carries out exponential filtering of MD data at each CD position. The MD estimate, defined as the mean value of a scan, is normally available only at the end of each scan. Some modifications of the basic approach allow MD estimates to be updated during each scan. More recent algorithms *(2, 4–9)* use stochastic models for the basis weight and moisture variations and can estimate CD (using a least-squares filter) and MD profiles (using a Kalman filter), with the MD estimations updated at each data point, therefore improving the possible MD control bandwidth. One such approach *(7)* is the estimation and identification of basis weight and moisture content (EIBMC) algorithm.

Recent trends in actuator design have allowed CD control systems for paper machines to involve an increased number of measurements and control signals. Increases in resolution for both sensors and actuators are the general trend. The increased resolution potentially leads to an improved overall control of paper machines if the multivariable control issues can be addressed effectively *(1)*. The increased amount of information causes problems in data processing (slowing the estimators and controllers), visualization of the process information, and in data storage. While the advances in computer technology tend to provide enough computing power, the visualization and data storage demands are becoming increasingly important. Machine operators depend on the clear presentation of process data to be able to detect any change in the quality of the final product, so an enhanced image of the two-dimensional (CD x MD) data is an important part of the operator interface. Enhancements may include data filtering to provide noise-free images or representations that extract particular features, e.g., sudden changes in paper quality, or streaks. This type of data processing leads to better diagnostics and feature recognition by human operators and potentially by the automated systems.



1. Wavelet filters used in the analysis

Quality control and production monitoring is increasingly important with the introduction of new standards (ISO 9001). Being able to record production conditions and to trace the events that caused a change in the paper quality have become essential for paper manufacturers. Data compression methods that provide efficient data storage and retrieval of records taken over long periods of time are desirable.

In this paper, a novel way of handling scanned paper machine data is presented. An effort has been made to provide a framework that unites the estimation, visualization, and data storage of the paper machine process data using wavelet analysis. These techniques have been adapted from results available in the image-processing literature. The results of the new method are compared to those obtained using the EXPO and the EIBMC algorithms.

WAVELET METHODS

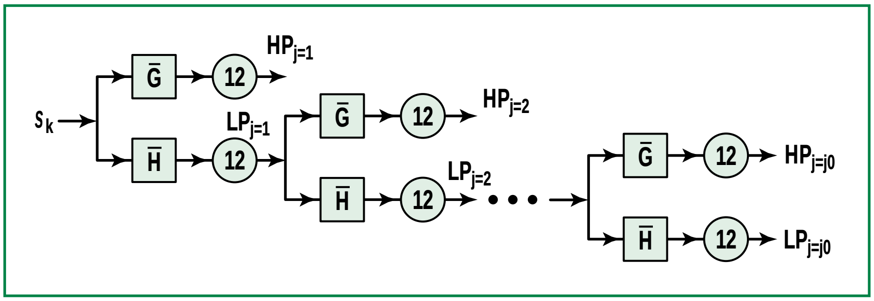
A signal can be approximated by a weighted sum of basis functions with the accuracy of the approximation depending on the class of signals, the choice of basis functions, and the number of terms. Different basis functions naturally lead to different representations. For example, the use of complex exponential basis functions in the Fourier transform reveals information about the frequency content of the overall signal but loses any ability to identify time-domain changes in the spectrum. On the other hand, the original signal representation by a sum of time-domain samples contains complete information about time-domain behavior but no spectral content.

An alternate set of basis functions is desirable if it is necessary to track changes in both spectral and time-domain characteristics. Wavelets provide one such set of basis functions, one that is created by scaling and translating a time-domain *mother wavelet* function. The original data are decomposed into images at these multiple resolutions. With the appropriate choice of wavelet, the decomposition can maintain good time resolution, possess good frequency resolution, and allow the exact reconstruction of the original data. Fundamental work in this area includes that of Daubechies *(10–12),* Meyer *(13, 14),* Cohen *(15),* and Wickerhauser *(16).* Wavelets are thus created by scaling and translating the prototype function $\Psi(x)$, the *mother wavelet.* The scale factor is normally chosen to be a power of 2, leading to a cascade octave band-pass filter structure. For the discrete wavelet transform, all integer shifts of $\Psi(x)$ are considered, and the wavelet decomposition of the signal $f(x)$ is given by the following equation:

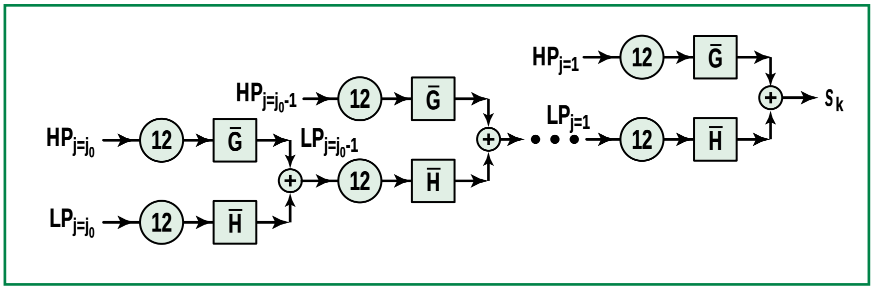
$$f(x) = \sum_j \sum_k c_{jk} \Psi_{jk}(x) \qquad (1)$$

where

$$\Psi_{jk}(x) = 2^{j/2} \Psi(2^j x - k) \qquad (2)$$



2. Block diagram of discrete wavelet transform



3. Block diagram of inverse discrete wavelet transform

Figure 1 shows some examples of mother wavelets possessing the required scaling and completeness properties. For more information about the mother wavelets used here, refer to the original papers *(11, 12, 17).* The problem of matching the appropriate wavelet to the signal and noise characteristics of a particular problem is complex and, at this stage, only general remarks can be made. The Haar wavelets are clearly well matched to piecewise constant signals and so to edge effects. Longer wavelets allow increased frequency resolution and are effective in smoothing. In all cases, the approach demonstrates excellent signal-to-noise improvement without the loss of resolution detail that is characteristic of conventional exponential filtering.

This area is also being rapidly developed. Techniques for recursive and adaptive process data analysis have been reported as have wavelet packet methods, which allow wavelet data decomposition to be applied at varying resolutions in different sectors of the time/frequency space *(18).*

Decomposition and reconstitution

The paper machine scanning sensor provides a sequence of discrete measured values. An efficient algorithm for applying the discrete wavelet transform (DWT) is provided by Mallat's pyramid algorithm *(19).*

Let the sequence s_k of values be of the length $n = 2^N$. The block diagram of a one-dimensional DWT is shown in **Fig. 2.** The transform requires two properly designed wavelet filters: $\bar{G}$, a high-pass filter, and $\bar{H}$, a low-pass filter, both of length *M.* The mother wavelet provides the prototype low-pass filter impulse response. These two filters are not independent, since

$\bar{g}_n = (-1)^{1-n}\bar{h}_{1-n}$, where $\bar{g}_n$ and $\bar{h}_n$

are the filter coefficients of $\bar{G}$ and $\bar{H}$,

respectively. The DWT is implemented by filtering the signal followed by down-sampling by a factor of 2.

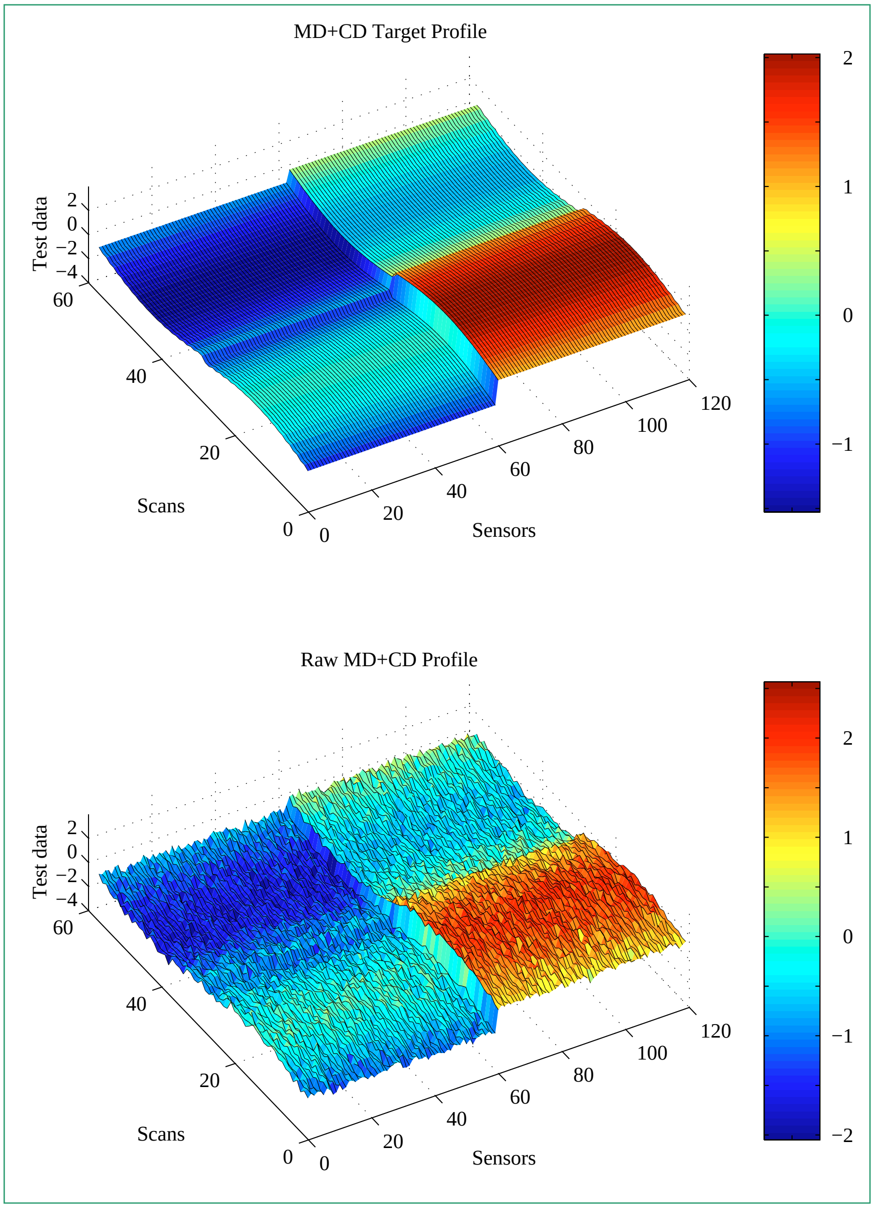
The inverse DWT, depicted in **Fig. 3**, is accomplished by up-sampling the high-pass and low-pass components by inserting a zero sample after each element, and convolving the up-sampled low-pass and high-pass signals with the filters *H* and *G,* respectively. The filter pair (*H*,*G*) is related to the forward DWT filter pair ($\bar{H}$,$\bar{G}$) by $g_n = \bar{g}_{-n}$ and $h_n = \bar{h}_{-n}$.

The wavelet representation of the signal can become very compact, with only a few coefficients being needed to represent a complex time function. In contrast, broadband components associated with noise have their energy dispersed over the coefficients. This property makes the wavelet transform very suitable for estimation and data compression. By manipulating the wavelet coefficients, it is possible to remove the less significant features of a signal while enhancing the components of interest. An estimated, noiseless signal can thus be obtained after the inverse DWT. The fact that the signal energy is concentrated in a relatively small percentage of its wavelet coefficients also naturally leads to the use of wavelets in data compression.

Thresholding

The term *denoising* is used widely to describe, in an informal way, the various schemes used to reduce the noise components of the original signal by damping or thresholding coefficients in the wavelet domain *(20).* Different methods of wavelet filtering are documented in the literature, with many implementations being based on the work of Donoho and Johnstone *(21–24),* who have shown that, for additive Gaussian white noise disturbances, nonlinear wavelet coefficient thresholding produces signal estimates that are nearly optimal.

There are two main types of thresholding: *hard thresholding* and *soft thresholding.* Hard thresholding leaves the magnitude of all wavelet coefficients greater than some threshold value unchanged, but sets all others to zero. Soft thresholding also sets the coefficients smaller than the threshold value to zero but then reduces the magnitude of the remaining coefficients by the threshold value. It is typical to apply thresholding only to the higher-resolution coefficient levels, keeping the lower-frequency content of the signal intact. It is clear that these thresholding methods are highly nonlinear.



4. Edge effects: CD and MD before and after noise addition

Donoho and Johnstone have established several approaches to threshold selection. The Universal Threshold or VisuShrink approach uses the threshold value given by $t_{univ} = \bar{\sigma}\sqrt{2\log(n)}$, where $\bar{\sigma}$ is the noise-level estimate. The same authors have also proposed the Median Absolute Deviation (MAD) method for estimating the noise level on the basis of the magnitude of the highest-resolution wavelet coefficients (ω_f). The standard deviation of the noise is estimated as σ = Median($|\omega_f|$)/0.6745, with the same threshold being applied to all the resolution levels. The MAD method leads to a robust estimator that is useful where visually appealing smooth images are desirable.

WAVELET FILTERING OF PAPER MACHINE DATA

A new set of Matlab functions and scripts has been developed to provide quick access to a variety of different wavelet denoising techniques and to different test data sets. This software had its genesis in the Rice University Wavelet Toolbox *(25)* and WaveLab *(26)*. However, the current version has been rewritten to adjust the algorithms to handle paper machine data. Arbitrary numbers of data boxes and scans are considered.

By selecting different options in the front-end interface, many different alternatives can be assessed. Both hard thresholding and soft thresholding have been tested. Following Donoho and Johnstone, the four different methods used for noise estimation and threshold selection are:

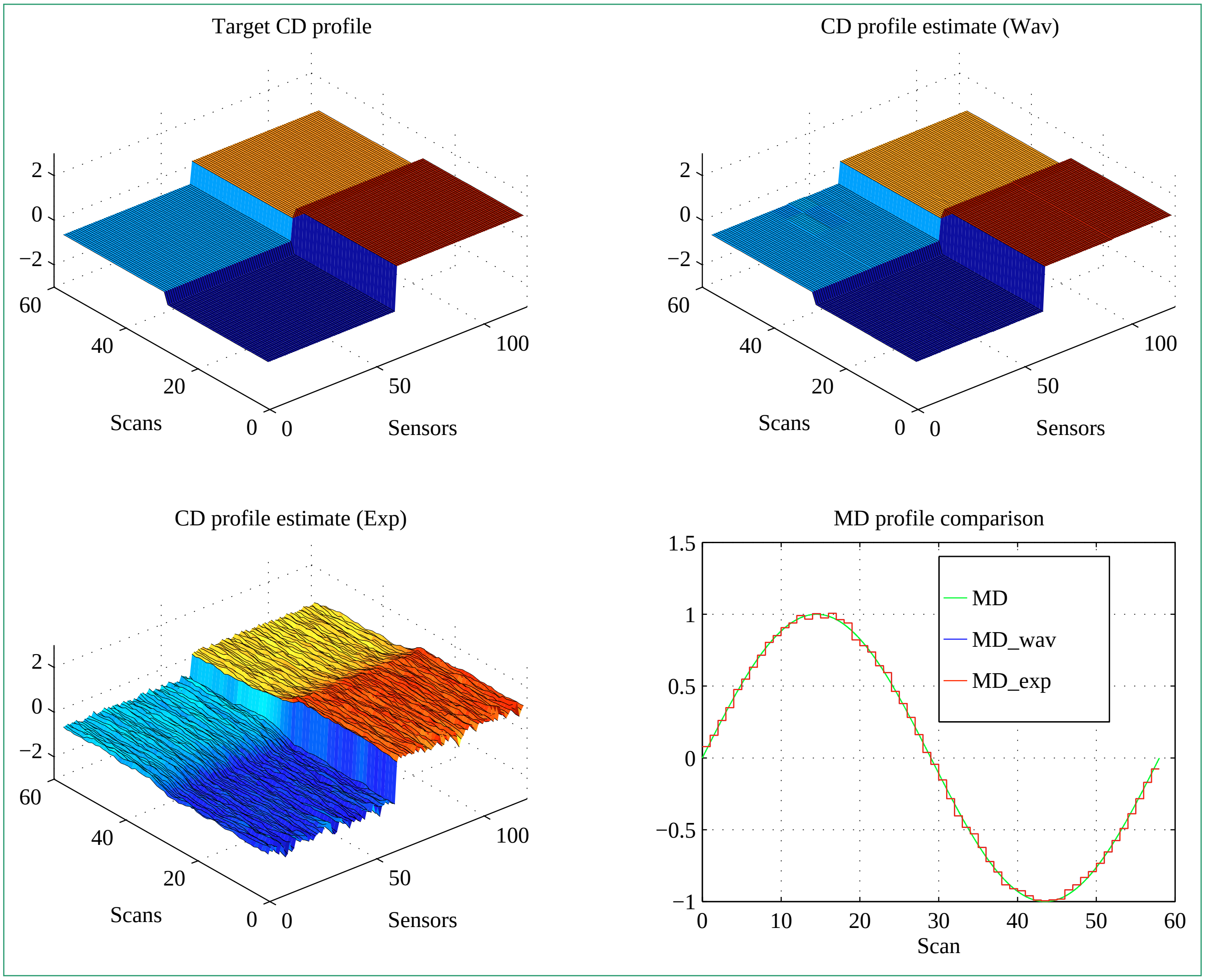
- A threshold value taken as the standard deviation of the wavelet coefficients at the finest resolution level multiplied by $[2 \cdot \log(n)]^{0.5}$
- The VisuShrink procedure
- The MultiMAD, resolution-dependent, thresholding approach, using the MAD noise estimator to estimate the noise standard deviation at each resolution level
- The SureShrink approach.

Filters created from four different mother wavelets are used: (a) the Haar wavelet, (b) Daubechies orthogonal wavelets, (c) Coiflets, and (d) Symmlets.

Results using various wavelet denoising procedures are compared with those obtained using the EXPO algorithm and, in some cases, with those obtained by the EIBMC algorithm. Only a few tests using the EIBMC algorithm were made since, unlike wavelet methods, the EIBMC algorithm needs to be carefully tuned to the test data sets. The verification process called for some extreme-case input signals. Note that both EIBMC and EXPO algorithms are recursive algorithms, whereas wavelet filtering is a batch operation at present.

Results using simulated data

The wavelet algorithms have been assessed using various sets of simulated data. The data sets were designed to provide signals with enough complexity to evaluate the estimator properly. The test data also contained features that commonly appear on the paper sheet, e.g., streaks, bumps, and grade changes. All the data sets have been



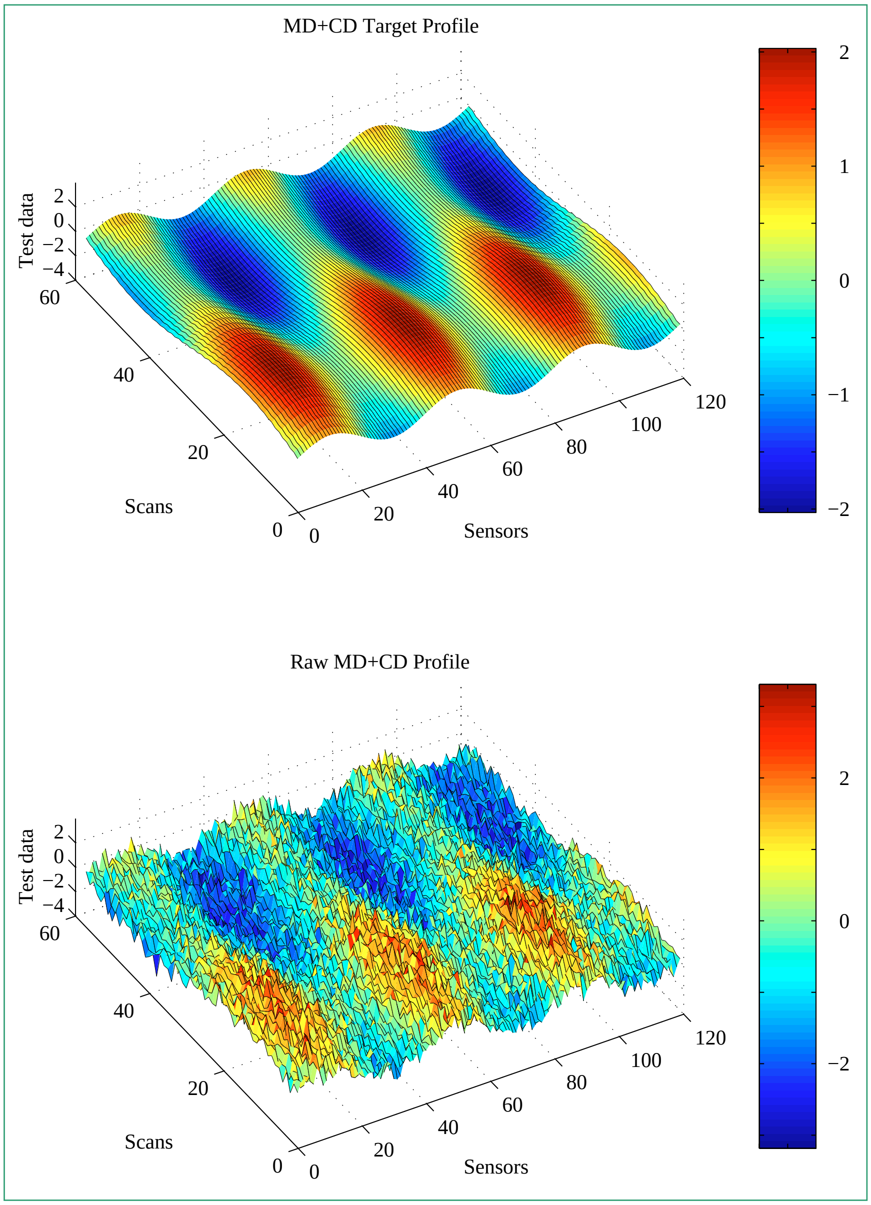
5. Edge effects: estimated profiles

zigzag sampled and presented to the estimator as if they had come from a paper machine scanner. The data processing is in batch mode.

Edges and step changes The first data set was created so that edge effects can be evaluated. Errors arise from the signal periodicity assumed by the DWT and from the need to pad the data set to a size $D(2^N,2^M)$ before processing. Edges also arise from sharp changes in MD and CD profiles. The target values (noiseless data) are shown in **Fig. 4**. This data set contains a well-defined CD profile, which differs greatly at the edge sensors (sensors 1 and 120) and has a sharp discontinuity at sensor 60. The MD profile is a sine function of time with unit amplitude. At MD position 29, the CD profile flattens by 50%. The number of scans for all test data sets is 58, and the number of sensors is 120. Consequently, four data points were required to be added at the ends of each CD profile, and three scans were padded before and after the real signal.

This signal is corrupted with white noise of variance $\sigma^2 = 0.2^2$. The composite signal, before and after adding noise, is also shown in Fig. 4. This noisy signal has been processed by different wavelet estimators, and the results have been compared to those obtained by the EXPO algorithm. For a signal containing abrupt changes in constant values, it is to be expected that the piecewise constant Haar wavelet will perform well. This has been confirmed by the experiments shown in **Table I**, where the errors resulting from the use of different wavelets and different thresholding methods are compared with those to be expected from exponential filtering. The estimated profiles and actual signals are given in **Fig. 5** for the case of Haar wavelets. MD variations are calculated as scan averages. Note that the results in Table I are not the best that could be obtained if the full range of wavelet and thresholding choices were examined and matched to a particular data set. A few typical combinations have been reported so that a fair comparison can be made for the analysis of later data sets.

Although the Haar wavelet used in this example has produced the best re-



6. Smooth surfaces: CD and MD before and after noise addition

Wavelet	Thresholding method	Threshold estimation	Wavelet length/type	Resolution levels	$\frac{J}{J_{expo}}$
Daubechies	Soft	Std.	6	3	0.85
Daubechies	Soft	MultiMAD	6	3	1.14
Symmlet	Soft	Std.	6	3	0.85
Symmlet	Soft	MultiMAD	6	3	1.19
Coiflet	Soft	Std.	3	3	0.83
Coiflet	Soft	MultiMAD	3	3	1.27
Haar	Soft	MultiMAD	2	2	0.46

I. Edge effects—summary of error results

sults, a variety of different configurations have also performed very well. When very smooth wavelet filters have been used, the estimation error increases, with an increased number of resolution levels as a result of the thresholding effects on the low-frequency part of the signal.

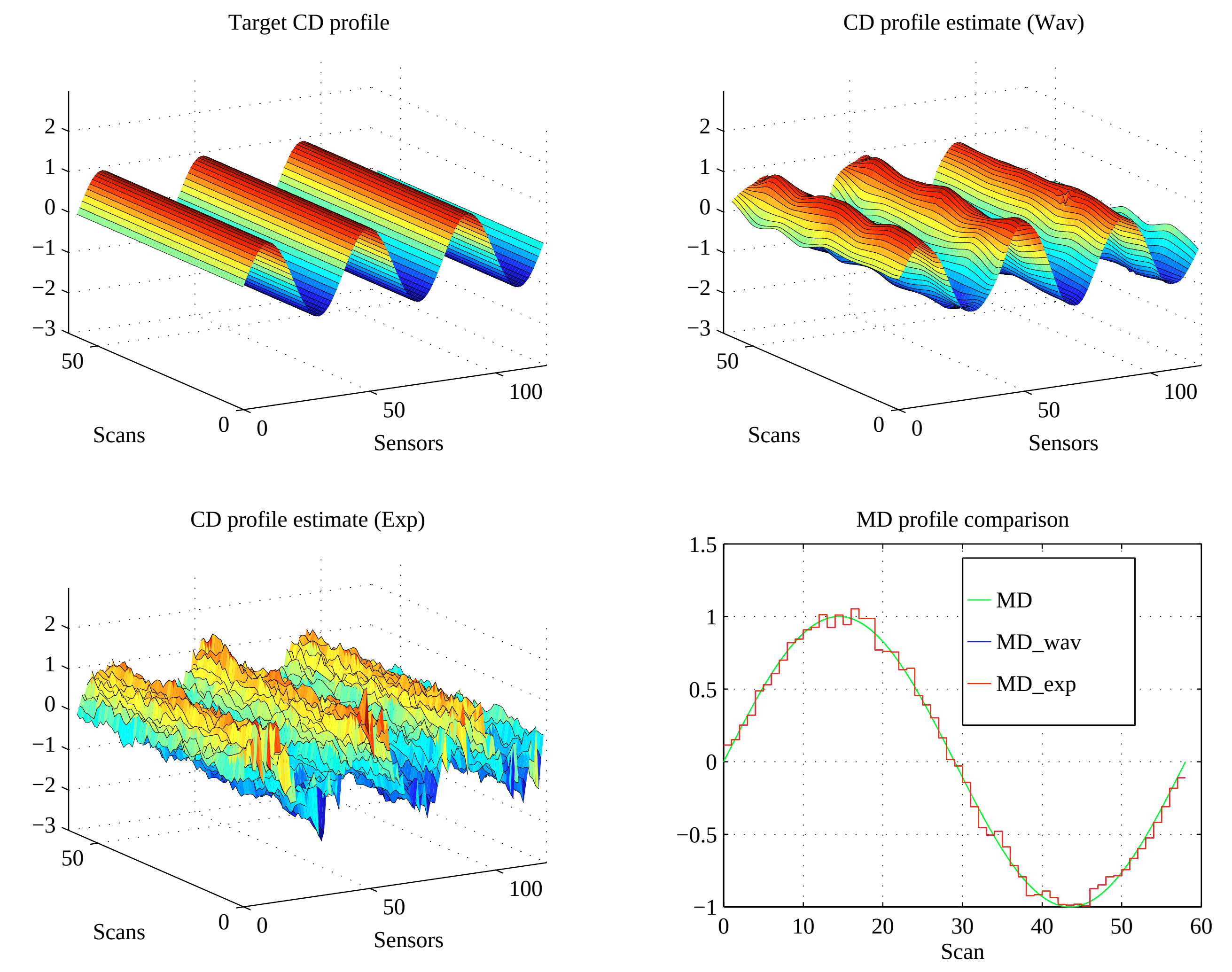
Smooth fluctuations The second data set, shown in **Fig. 6**, has been created with the intention of testing the wavelet estimator on some smoother surfaces with a constant signal-to-noise ratio. The profiles were corrupted by additive white noise of variance $\sigma^2 = 0.5^2$, significantly higher than in the first data set.

As expected, the Haar wavelet no longer produces the best performance. In **Table II**, the Symmlet is now shown to be superior, although the Haar wavelet still outperforms exponential filtering. Note that the performance can be compared with the results shown in Table I for the same algorithms on different data. **Figure 7** shows that both CD and MD variations are accurately detected in spite of the high noise levels.

Results using industrial data

In most cases, the selected group of wavelet estimators performed significantly better than the exponential filtering. The testing also shows that the method is robust in the sense that the choice of filter from the selected group (given in the tables showing the summary results) is not critical to achieving good performance. When the features of interest are known (e.g., when looking for certain patterns on the sheet), the most effective wavelet estimator can be selected and matched to the particular job. In this way, a substantially better performance (compared to the conventional estimators) can be achieved.

The industrial data set was collected from a pulp machine *(2)* with a target basis weight of 640.6 g/m². The slice lip opening at the headbox was 15 cm. The machine was 4.43 m wide with design speed of 184 m/min. The CD moisture control system was a Devronizer with 25 actuators, each 15.24 cm wide. One scan took 34 seconds to complete. Two known DC actuator bumps are applied: the first at a location corresponding to sensor 20 during scans 19–31 and the second corresponding to sensor 87 during scans 13–30.



7. Smooth surfaces: estimated profiles

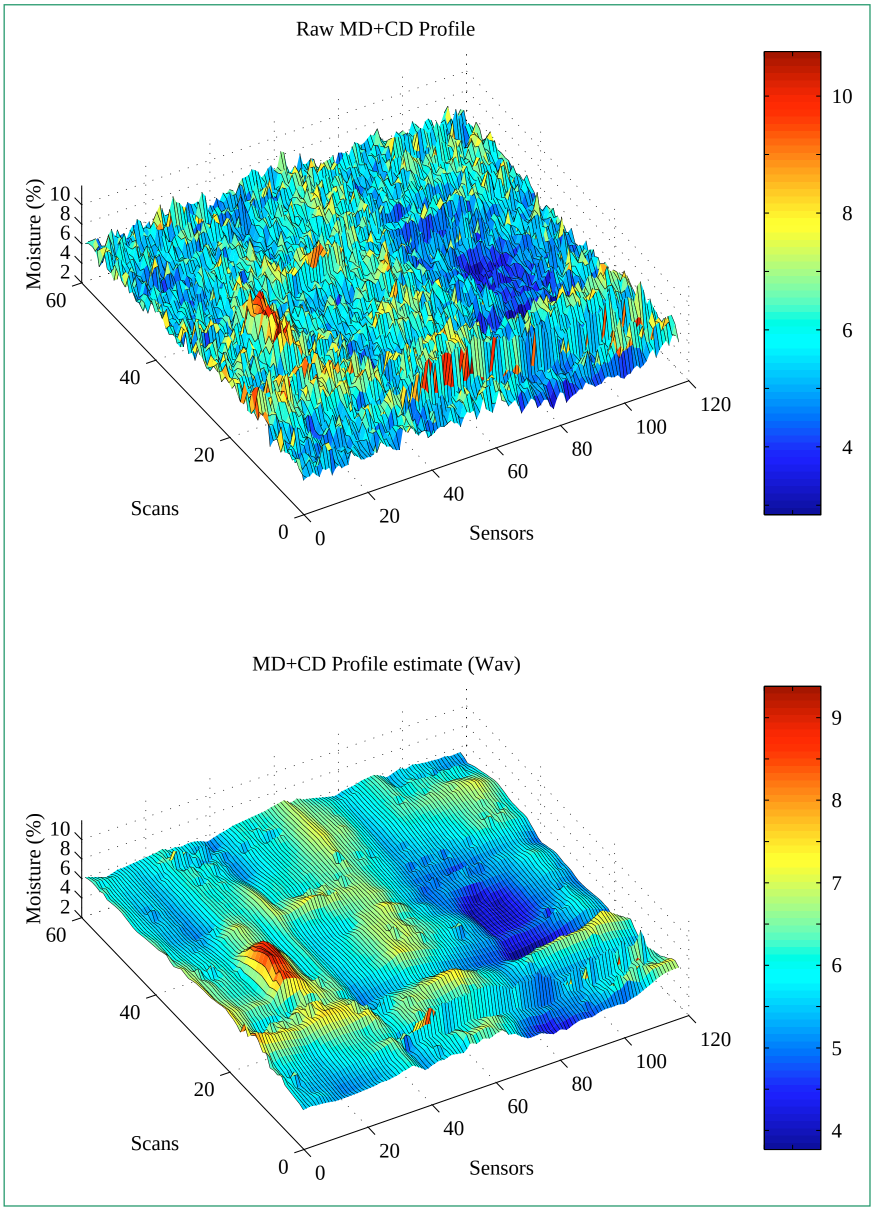
In this case, only three different wavelet estimators were compared to the EXPO and EIBMC approaches. The estimators chosen are given in **Table III**. The first estimator produced the results given in **Figs. 8 and 9**. This filter yielded very smooth results. Note that the CD streak that can be seen in scan 8 was identified in the CD profile by the wavelet filter but was lost to exponential smoothing. To assess the effect of less smoothing in the low-frequency range, the number of resolution levels for the other two cases has been dropped to two. During the experiments, it has been observed that the adaptive wavelet filtering methods work more reliably when the number of resolution levels has been kept low. It is well known *(21, 24)* that, for adaptive filtering to

Wavelet	Thresholding method	Threshold estimation	Wavelet length/type	Resolution levels	$\frac{J}{J_{expo}}$
Daubechies	Soft	Std.	6	3	0.51
Daubechies	Soft	MultiMAD	6	3	0.51
Symmlet	Soft	Std.	6	3	0.39
Symmlet	Soft	MultiMAD	6	3	0.39
Coiflet	Soft	Std.	3	3	0.42
Coiflet	Soft	MultiMAD	3	3	0.42
Haar	Soft	MultiMAD	2	2	0.95

II. Smooth surfaces—summary of error results

Wavelet	Thresholding method	Threshold estimation	Wavelet length/type	Resolution levels
Daubechies	Soft	Std.	6	3
Daubechies	Soft	MultiMAD	6	3
Symmlet	Soft	MultiMAD	6	2

II. Smooth surfaces—summary of error results



8. Pulp machine moisture data: raw and filtered data

work well, the number of resolution levels used for denoising must be kept well below the maximum possible number of decomposition levels.

The second and third wavelet filters show superior performance compared to the conventional estimators in identifying the location of bumps, as seen **Figs. 10 and 11**. The locations of the real bumps, based on the known positions of the actuators and their widths, were 13 x 4.8 and 18 x 4.8 for the first and the second bumps, respectively. Both the EXPO and EIBMC algorithms disperse the bumps over a greater number of scans, although the width is preserved. The wavelet estimators have therefore identified the location and amplitude of the bumps more accurately.

DATA COMPRESSION

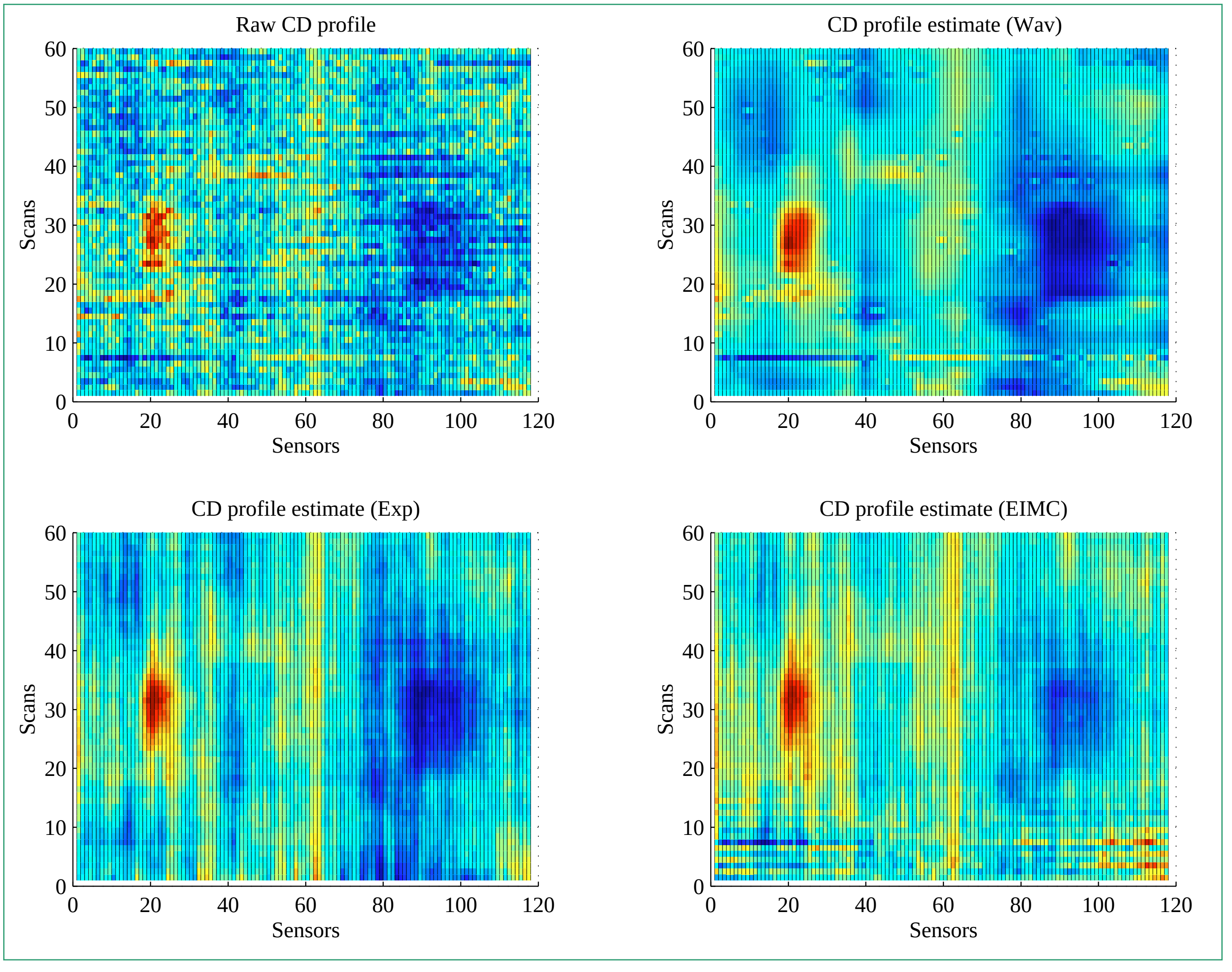
Data compression is one of the most important applications of wavelet theory since, under appropriate conditions, the DWT compresses the signal representation so that only a relatively small number of coefficients is needed for accurate reconstruction. There are two basic types of data compression: lossless and lossy. *Lossless compression* allows an exact reconstruction of the signal. In contrast, *lossy compression* allows small errors in the reconstruction in an attempt to achieve higher compression ratios.

Here, we consider only lossy compression, since the goal is to reconstruct only the signal from the noisy data. Ideally it is the signal that is reconstructed, and the loss should be the noise. The denoising procedures reduce the number of nonzero coefficients, increasing the degree of compression.

Two levels of data compression are possible. One method is to use the procedure depicted in **Fig. 12**. Here, sparse matrix methods exploit the effects of thresholding. The role of the encoder is to losslessly compress the sparse matrix of quantized coefficients. For fast execution, simple run-length Pratt coding *(27)* of zero-valued coefficients is effective. This simple procedure, when applied to industrial data, has been found to provide a compression ratio of 13:1. Five percent of the coefficients are nonzero following thresholding, and the remaining coefficients can be stored using a sparse matrix routine. Because the wavelet transform and thresholding procedures are an integral part of the estimator, no additional computing time is required.

Another method used in image compression is shown in **Fig. 13**. This method includes quantization of the nonzero DWT coefficients and so results in higher compression ratios, albeit it at the expense of additional error. A quantizer maps the set input values into a smaller set of output values, commonly using a staircase function. A continuous variable u maps into a discrete variable u^*, which takes values from a finite set of reconstruction levels $\{r_1, r_2, \ldots, r_L\}$, as discussed by Jain *(28)*.

If the value of u is between two decision levels, the quantizer will map it into one of the two reconstruction



9. Pulp machine moisture data: estimated profiles (Daubechies 6,3)

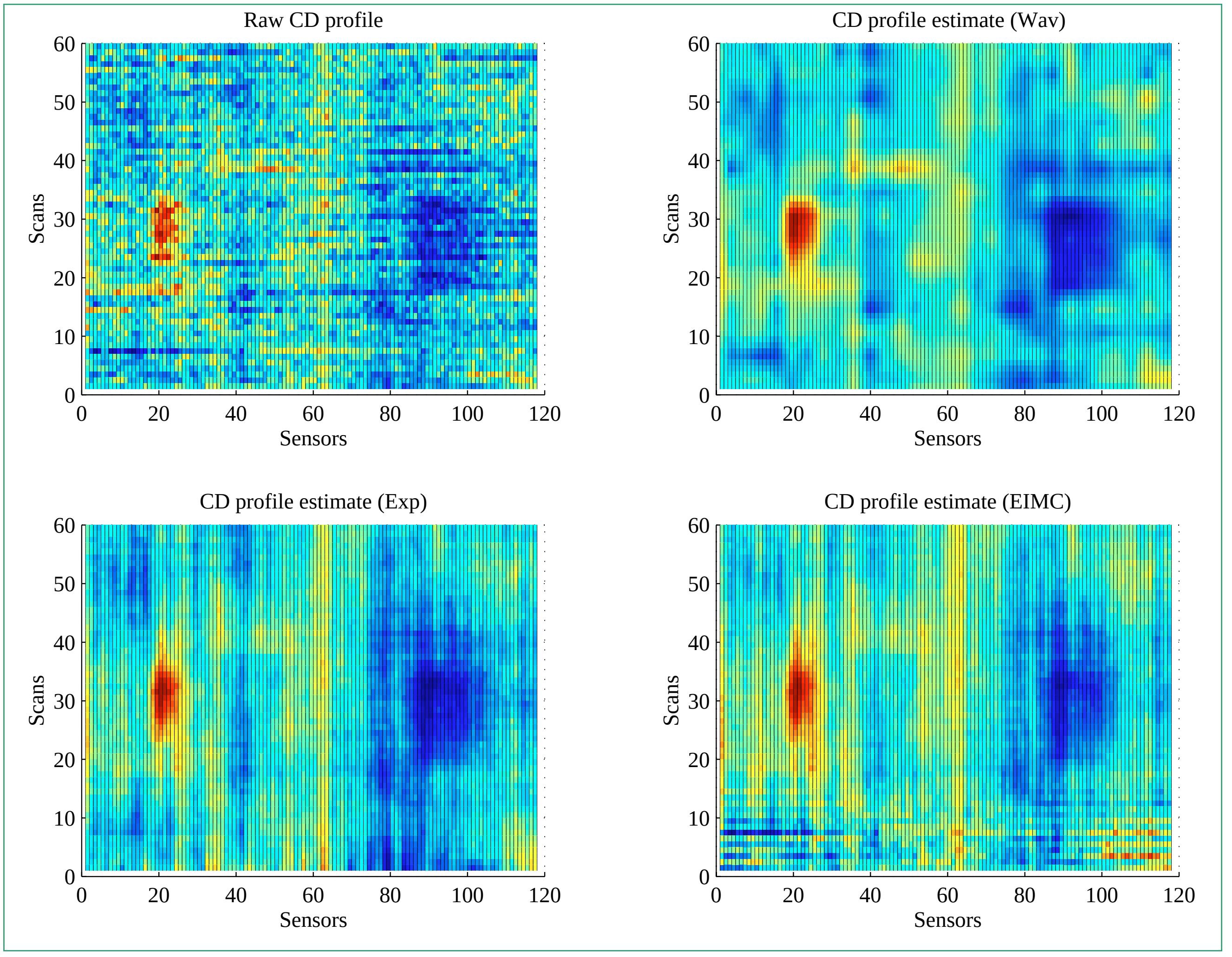
levels. The quantizer mapping is thus irreversible, since the original value cannot be uniquely determined during reconstruction. The quantizer should be designed to minimize distortion. In the case of the wavelet transform, where the most significant information about the signal is carried by the high-magnitude wavelet coefficients, the quantizer should have more reconstruction levels dedicated to those amplitudes. One method, the Optimum Mean Square Quantizer (LLOYD-MAX) design, is given in the literature *(28).*

The decompressor shown in Fig. 13 applies decoding (unique) and dequantization (nonunique) to generate a set of wavelet coefficients. Note that compression of process data differs from compression in image processing. Image-processing compression optimizes to account for the human visual system *(29),* while the goal of process data compression is to preserve information about a chosen characteristic of the process. Additional information on wavelet data compression may be found in the overview given by Hilton *(30).*

Compression of paper machine data

Some of the more practical aspects of process-data compression are now addressed. Compression both with and without quantization has been considered. It has been assumed that the input data have been measured and stored in 16-bit format. All the calculations have been carried out using double-precision calculations. Three resolutions have been used for test purposes: 8-, 12-, and 16-bit. The 16-bit resolution has been used as the reference, yielding the compression ratio of 1:1. The 12-bit resolution thus corresponds to a compression ratio of 1.33:1, and the 8-bit resolution yields a compression factor of 2:1. In all cases, the quantization is applied to the range of values occupied by each data set. These compression ratios are in addition to those achieved by thresholding of the wavelet coefficients and by sparse matrix encoding.

As a first example of the data compression achieved, the wavelet filters shown in **Table IV** are applied to the simulated data representing smooth variations that were discussed in the previous section. **Table V** shows the compression ratios achieved for each wavelet filter and resolution level.



10. Pulp machine moisture data: estimated profiles (Daubechies 6,2)

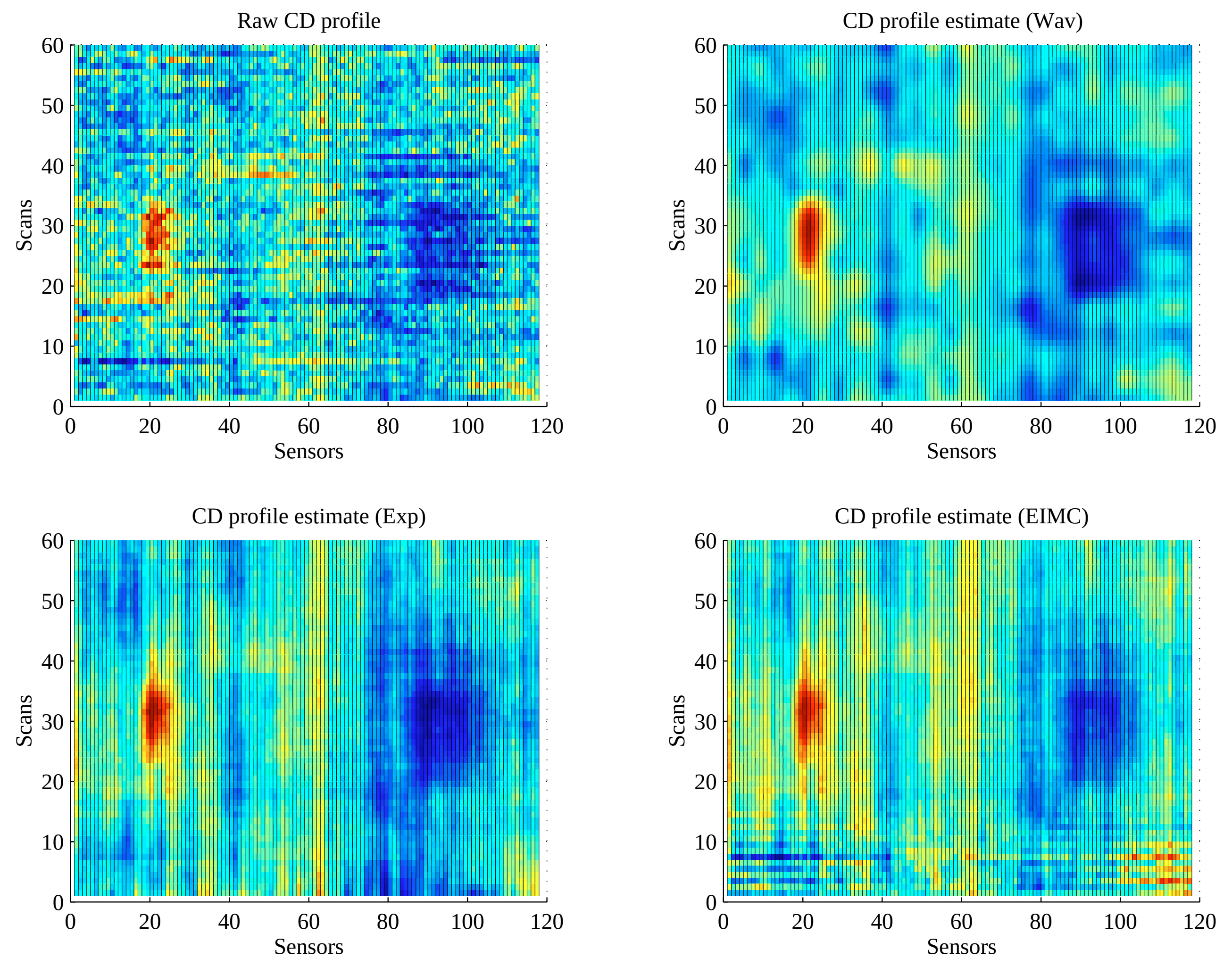
Case	Wavelet	Threshold estimation	Wavelet type/length	Resolution levels
1	Daubechies	Std.	6	3
2	Daubechies	MultiMAD	6	3
3	Symmlet	Std.	6	3
4	Symmlet	MultiMAD	6	3
5	Coiflet	Std.	3	3
6	Coiflet	MultiMAD	3	3
7	Haar	MultiMAD	2	2

IV. Filters used for industrial data sets

With an appropriate filter choice, compression ratios of up to 100:1 are achieved. Note that only the Haar wavelet results in a significantly lower compression, and so the choice of wavelet is not critical here. Also, the accuracy of the wavelet filters, in comparison with the exponential standard, is not jeopardized by quantization. Even at the 8-bit level, if the Haar wavelet is excluded, all cases result in at least a 33% improvement.

The three filters described earlier in Table III were again applied to the industrial data set to evaluate the effectiveness of the compression methods in practice. Although the results are less dramatic than on the test data, and naturally the increase in error cannot be evaluated, compression ratios of roughly 27:1 were obtained.

Figure 14 graphically shows the manner in which wavelet transformation and then thresholding enable the quantized information to be concentrated into relatively fewer coefficients. In each case, the coefficient frequency of occurrence is plotted against quantization level. As would be expected, the original data, shown in Fig. 14(a), is smoothly distributed about a mean value. Note the frequency scale in comparison with the two lower plots. The center plot, Fig. 14(b), shows how the wavelet transform has separated the signal into two components, one of which is characterized by a large number of coefficients close to zero. Thresholding removes most of



11. Pulp machine moisture data: estimated profiles (Symmlet 6,2)

Case	16-BIT Compress. ratio	16-BIT $\frac{J_{compress}}{J_{expo}}$	12-BIT Compress. ratio	12-BIT $\frac{J_{compress}}{J_{expo}}$	8-BIT Compress. ratio	8-BIT $\frac{J_{compress}}{J_{expo}}$
1	50.43	0.51	67.25	0.51	100.87	0.66
2	50.80	0.51	67.74	0.51	101.87	0.66
3	49.36	0.39	65.82	0.39	98.72	0.51
4	51.56	0.39	68.74	0.39	103.11	0.51
5	49.01	0.42	71.38	0.42	107.08	0.42
6	53.54	0.42	71.38	0.42	107.08	0.42
7	13.57	0.95	18.09	0.95	27.13	0.96

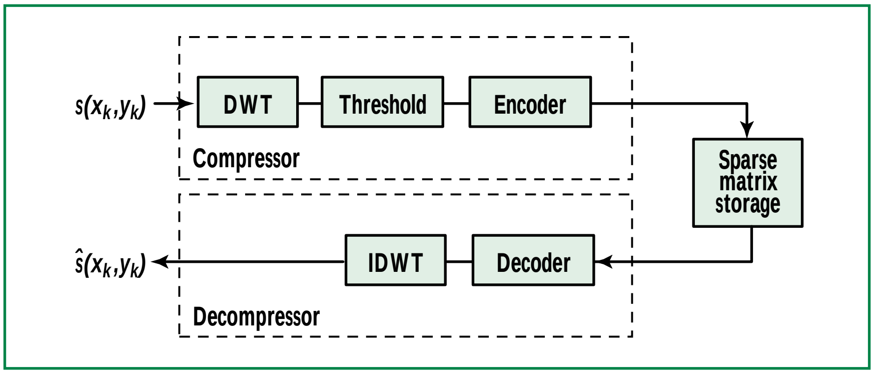
V. Smooth surfaces—summary of compression results

the low-value coefficients in Fig. 14(c), with only 513 of the original set of 8192 nonzero coefficients remaining. Note the substantially reduced frequency scale. Visually, the compressed representation cannot be distinguished from the original.

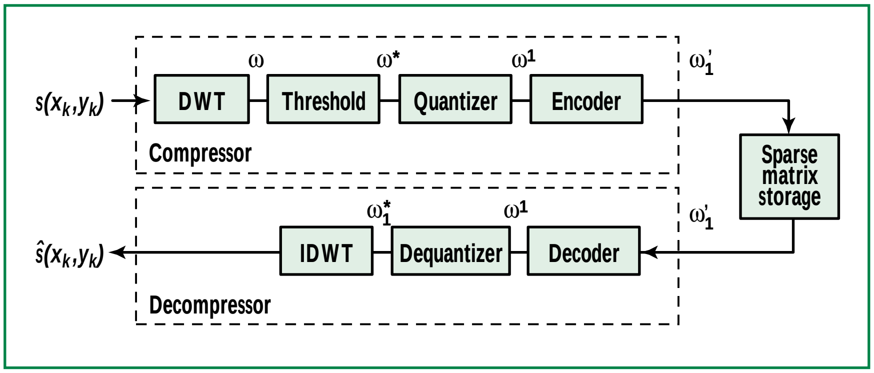
CONCLUSIONS

The paper describes a new approach to paper machine process data analysis using one- and two-dimensional discrete wavelet transforms. These techniques have been adapted from a general theory that has been developed in recent years on the application of wavelets to image and signal analysis. Application areas in which the theory was first applied have included image processing and bandwidth compression for communications.

An analysis of the use of wavelets for processing scanned data repre-



12. Block diagram of a compressor/decompressor without a quantizer



13. Block diagram of a compressor/decompressor with a quantizer

senting basis weight and moisture variations on a paper machine has been carried out. It has been shown that wavelets are effective for detecting process changes in scanned and noisy data, leading to better estimation and visualization of the machine-direction and cross-direction variations. For appropriate choices of wavelets, profile estimates are improved over those obtained using exponential filtering or other standard analysis methods.

The second main attribute of the method is that it allows compression of the process data without significantly diminishing the ability to reconstruct accurate profiles. It has been shown that the compression method can be embedded into the estimation algorithm, producing excellent results without a major increase in the computation time. The ability to reduce data storage requirements is of importance in millwide process-monitoring systems.

Comprehensive testing of the proposed algorithms has been carried out on a variety of simulated data sets for which the true process variations are known. Industrial data have also been analyzed, and the method had many desirable characteristics.

The following properties have been shown for the wavelet estimator:

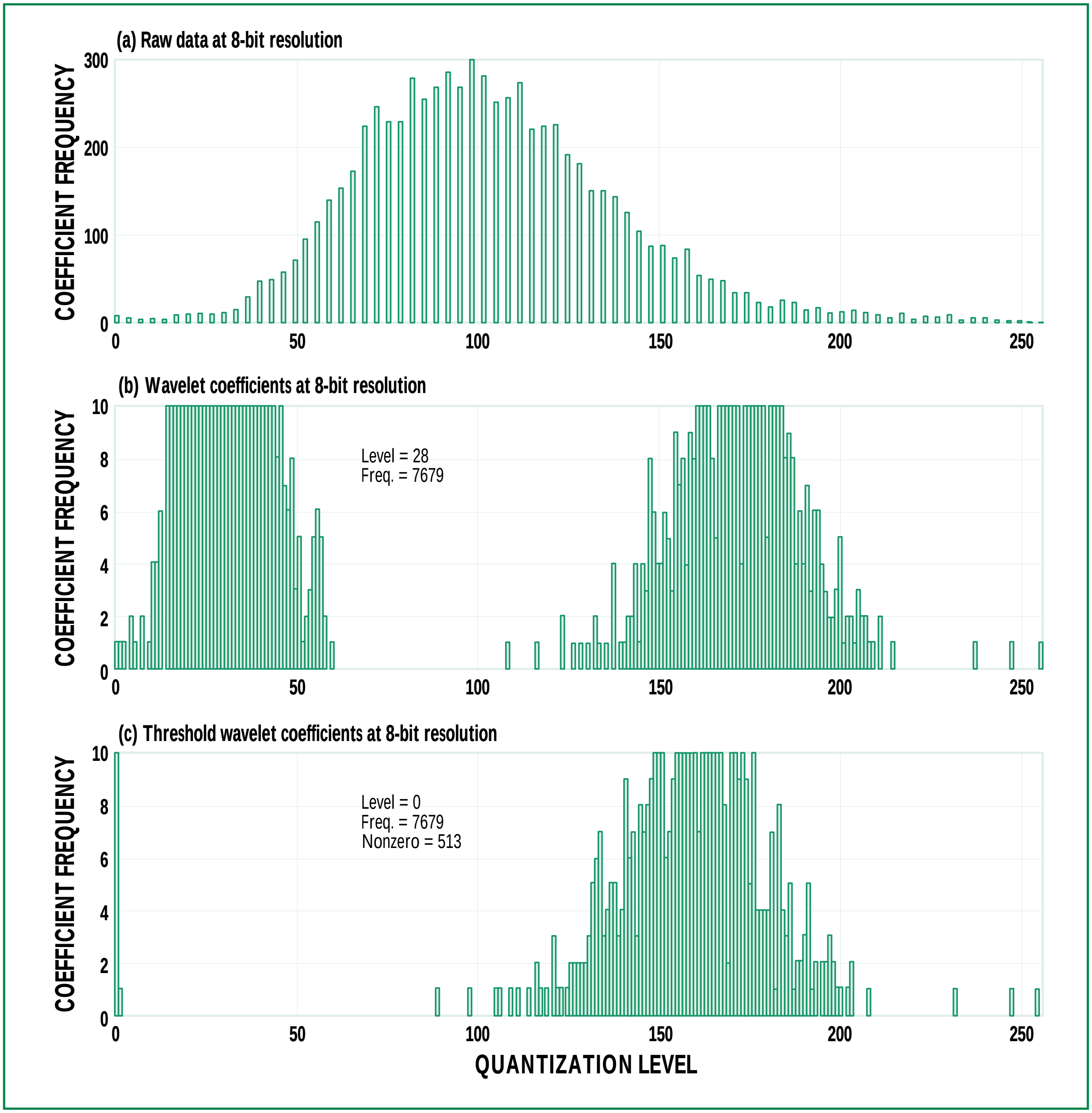
- When applied to test data, the estimator improves the accuracy of estimation, compared to existing algorithms.
- When applied to industrial data, the method presents an excellent visual interface to the papermaking process.
- The wavelet decomposition can be closely related to cross-direction actuator responses. It is expected that a cross-direction control method based on an appropriate wavelet analysis will allow profile upsets to be matched to actuator settings.
- The algorithm is computationally fast; this allows real-time analysis. The need for a recursive form may be avoided.
- The method is shown to be applicable to basis weight and moisture estimation using data from a scanning sensor. It could most likely be used for analyzing other process variables.
- Unlike many estimation methods based on least-squares techniques, wavelet analysis is robust in its performance and does not require additional tuning once it has been properly installed.

The compression results show the following points:

- The method achieves compression ratios greater than 25:1 (up to 100:1) while maintaining lower errors than an exponential filter-based algorithm.
- Data compression can be incorporated as an integral part of the estimator procedure, adding little additional computational effort.
- The algorithm provides an effective tool for visualizing production variations over large time periods.
- The algorithm can be adjusted to provide either a minimum error or a constant compression ratio, allowing it to be tailored to particular applications.
- These methods will have value with the introduction of new, high- speed sensors generating large volumes of data. A related advantage is the ability to reduce time for data transfers over the local-area networks used in modern machines. **TJ**

KEYWORDS

Algorithms, analysis, basis weight, bibliographies, cross direction, data, estimation, machine direction, machinery, moisture content, paper machines, paper making equipment, variations, waves, weight.



14. Pulp machine moisture data: energy distribution

Nesic is a research engineer and Davies and Dumont areprofessors at The University of British Columbia, Pulp and Paper Centre, 2385 East Mall, Vancouver, BC V6T 1Z4, Canada.

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