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〈Research Paper〉

Analysis and Compression of Spun-yarn Density Profiles using Adaptive Wavelets

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Abstract — A data compression system has been developed by combining adaptive wavelets and optimization technique. The adaptive wavelets were made by optimizing the coefficients of the wavelet matrix. The optimization procedure has been performed by criteria of minimizing the reconstruction error. The resulting adaptive basis outperformed such conventional basis as Daubechies-5 by 5 ~10%. It was also shown that the yarn density profiles could be compressed by over 95% without a significant loss of information.

Keywords: *wavelet transform, textile data management, data compression, process dependent basis, factorization*

1. Introduction

For an on-line process control in spun yarn production, large amount of data must be compressed by discarding redundant information while the data are being captured.

Although research in quality monitoring and control system development has advanced over the past twenty years, a reliable system has yet to be developed mainly due to the high dimensionality of the data produced[1,2]. In recent times, some researchers have been focussing on works for designing on-line data reduction system by using stochastic analyses and wavelets[3,4] The detection and identification of imperfections or spinning faults during yarn manufacturing was also possible under the monitoring scheme developed. The use of wavelet transform is relatively good in textiles. Although they have been used extensively used in other fields such as mathematics and electrical engi neering where they have proved to be a reliable tool for signal characterization and compression[5].

The results were quite successful in that it could achieve a large amount of data reduction without any significant loss of information[6]. In this paper, a more improved data compression system will be developed for monitoring spinning process by using adaptive wavelet methodology.

2. Development of Process Dependent Bases

For compact representation of a yarn density signal, use of the right basis is one of the most important factors. The performance of many algorithms for optimal selection of wavelet basis is heavily dependent on the properties of basic wavelet used for transform. Obviously, the choice of wavelet basis plays an important role in achieving a large amount of data reduction and compression. So-called adaptive wavelet analysis deals with an algorithm for designing new wavelet functions and focuses on choosing an optimal set of wavelet coefficients. Given a signal of finite length(e.g. yarn density profiles) and an analysis objective(e.g. data reduction and compression), we proceed by determining the quantities to measure in order to achieve the objective.

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Recently, it was reported that optimal filter coefficients could be made by optimizing over the parameters which produce the filter coefficient matrix[7]. The new scheme makes the optimization routine simpler and computationally more efficient.

In this paper, we construct a library of waveforms whose members have desirable properties well matched to a specific signal (process) based on the algorithm. We call it "**a process dependent basis"** because it is constructed in a way of being optimized for a yarn made by a specific process. As a result of the optimization, more energy will be concentrated on fewer coefficients, which means more compact representation and thus data reduction.

Based on the optimization procedure, a specific wavelet basis will be constructed for different textile processes such as ring-spun, open-end and high-draft yarn manufacturing processes.

2.1. Design of Wavelet Matrices

In this section, general procedure for partitioning of the wavelet matrices is based on the literature[7]. For the general *m*-band discrete wavelet transform, a wavelet filter consists of one low pass filter, and *m-1* high pass filters. Ordinary wavelet transform is a specific case of the m-band transform when m is set to 2. Considering 3-band discrete wavelet transform with one low pass filter (h) and 2 high pass filters (g), each containing six coefficients (n=6), such that $h=(h_0),\ldots,h_5)$, and $g^{(1)}=(g_0^{(1)},\ldots,g_5^{(1)})$, and $g^{(2)}=(g_0^{(2)},\ldots,g_5^{(2)})$. The transformation from an original signal $\mathbf{x}_{(0)}$ (the highest scale) to next scale $\mathbf{x}_{(1)}$ is calculated by

$$x_{(1)} = W^{(0)}x_0 = P^{(0)}W^{(0)}_{cir}x_0$$
$$= (a_{10}a_{11}a_{12}d^{(1)}_{10}d^{(1)}_{11}d^{(1)}_{12}d^{(2)}_{10}d^{(2)}_{11}d^{(2)}_{12}) \quad (1)$$

where, $a_{j+1,k}=\sum_{i=0}^{n-1}h_i a_{j.mk+i}$, $d_{j+1,k}=\sum_{i=0}^{n-1}g_i^b a_{j.mk+i}$, $b=1,\ldots,m-1$.

There are certain restrictions which must be imposed upon the filter coefficients so that a MRA and wavelet basis exist. These conditions are summarized as follows[8]: 1) orthogonality $\Sigma A_k A_{k+1}^T=\delta_{0i}I$, Where δ_{0I} is kronecker delta, I is the identity matrix, 2) the regularity condition $\sum_k h_k=\sqrt{3}$, and 3) Lawton Matrix $M_{ij}=\sum_k h_k h_{k+j-mi}$ which must have an eigenvalue equal to one.

2.2. Process Dependent Basis

In this section, we develop an adaptive wavelet well-fitted to specific yarn density profile.

Specifically, we are interested in optimizing coefficients of wavelet filters for maximizing the compression performance. We consider the factorized form of a wavelet matrix instead of optimizing over each element in A in order to reduce the parameters to be optimized.

Given integers $m\geq 2$ and $k\geq 1$, any m x *mk* matrix *A* satisfying the orthogonality condition can be written in the factorized form[7]:

$$A=(A_0A_1\ldots A_{k-1})=H\circ F_1\ldots\circ F_q \quad (2)$$

where, symbol o represents the "polynomial product" which is defined by

$$(B_0C_1\ldots C_{p-1})\circ(C_0C_1\ldots C_{r-1})=(D_0D_1\ldots D_{p+r-2})$$
$$D_j=\Sigma_k B_k C_{j-k} \quad (3)$$

The factors $F_j=(P_j \quad I-P_j)$, where P_j is a symmetric projector $P_j=P_j^T=P_j^2$, and $H=\Sigma_j A_j$is an orthogonal matrix (HH^T = I). For a simple 2-band transform with a filter length of 4, if the orthogonality condition is satisfied, then[8]

$$A=H\circ F_1=H\circ(R_1 I-R_1)H(I-R_1)]=[A_0A_1] \quad (4)$$

Next step is to find H and projection matrix R_i (for *i=1, ⋯; k*) by factorization of matrix A. The regularity condition leads us to set the first row of H to $1/\sqrt{m}$ 1, where **1** denotes a vector of ones.

The remaining *m-1* rows of matrix *H*are calculated by maintaining the orthogonality of matrix H.

A symmetric projection matrices of rank can be written $R=VV^T$, where $V_{mx\tau}$ is a matrix with orthonormal columns. It has been well known from a literature that for wavelet matrix to be non-redundant, the ranks of the projection matrices have to form a monotonically increasing sequence. That is where the $rank(R_1) \leq .... \leq rank(R_k)$. Some restriction (i.e. rank is one) is usually placed on the projection matrices, and so we have also followed it.[7]

$$R_i = v_i v_i^T$$

where, $v_i^T v_i = 1$

Finally, we obtain both an orthogonal matrix H and projection matrices which are needed for constructing the wavelet matrix. The wavelet matrix can be constructed by normalized vectors $v_1, \cdots; v_k$ and u which are generated randomly from the uniform distribution.

For 2 band wavelet transform with 12 filter length to be employed in the paper, the algorithm is as follows:

Let

$Q_i = (I-R_i)$, $P_1=(R_1-2R_1R_2+R_2)$ and $P_4=(R_4-2R_4R_5+R_5)$, where I is an (2x2) identity matrix.

$$\begin{aligned} A &= H \circ F_1 \circ F_2 \circ F_3 \circ F_4 \circ F_5 \\ &= H \circ (R_1 \quad I-R_1) \circ (R_2 \quad I-R_2) \circ (R_3 \quad I-R_3) \circ (R_4 \quad I-R_4) \circ (R_5 \quad I-R_5) \quad (6) \\ &= [H * A_1 \ H * A_2 \ H * A_3 \ H * A_4 \ H * A_5 \ H * A_6, \end{aligned}$$

where $A_1 = R_1R_2R_3R_4R_5$,

$A_2=R_1R_2(R_3P_4+Q_3R_4R_5)+P_1R_3R_4R_5$,

$A_3=R_1R_2(R_3Q_4Q_5+Q_3Q_4)+P_1(R_3P_4+Q_3R_4R_5)+Q_1Q_2R_3R_4R_5$,

$A_4=R_1R_2Q_3Q_4Q_5+P_1(R_3Q_4Q_5+Q_3P_4)+Q_1Q_2R_3P_4+Q_3R_4R_5)$,

$A_5=P_1Q_3Q_4Q_5+Q_1Q_2(R_3Q_4Q_5+Q_3P_4)$ and

$A_6=Q_1Q_2Q_3Q_4Q_5$.

Since matrix H is fixed as $\begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$ or $\begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$ for 2 band wavelet transform, matrix A can be easily constructed by taking the different combinations of the five R vectors. The unit vector R_i can be generated from any vector $[a\ b]^T$ which satisfies $a^2+b^2=1$. As an example, the vectors are $[1\ 0]^T$ and $[0.6\ 0.8]^T$. By updating the five unit vectors R_i, optimal filter coefficients are constructed which satisfy a certain optimization criteria.

As a numerical example for constructing wavelet matrix A, a detail procedure is shown as follow:

1. Generate five uniform random numbers a_1=0.9501, a_2=0.2311, a_3=0.6068, a_4=0.4860 and a_5=0.8913.
2. Construct five matrices $b_1^2 = 1 - a_1^2$, $b_2^2 = 1 - a_2^2$, $b_3^2 = 1 - a_3^2$, $b_4^2 = 1 - a_4^2$ and $b_5^2 = 1 - a_5^2$.
3. $v_1=[0.9501\ \ 0.3119]^T$, $v_2=[0.2311\ \ 0.9729]^T$, $v_3=[0.6068\ \ 0.7948]^T$, $v_4=[0.4860\ \ 0.8740]^T$ and $v_5=[0.8913\ \ 0.4534]^T$, where $v_i = [a_i\ \ b_i]$.
4. $Q_1=(I-R_1)$; $Q_2=(I-R_2)$; $Q_3=(I-R_3)$;$Q_4=(I-R_4)$;$Q_5=(I-R_5)$;$P_1=(R_1-2R_1R2+R2)$;$P_4=(R4-2R_4R_5+R_5)$;
5. $A_1=R_1R_2R_3R_4R_5$
   $A_2=R_1R_2(R_3P_4+Q_3R_4R_5)+P_1R_3R_4R_5$
   $A_3=R_1R_2(R_3Q_4Q_5+Q_3P_4)+P_1(R_3P_4+Q_3R_4R_5)+Q_1Q_2R_3R_4R_5$
   $A_4=R_1R_2Q_3Q_4Q_5+P_1(R_3Q_4Q_5+Q_3P_4)+Q_1Q_2(R_3P_4+Q_3R_4R_5)$;
   $A_5=P_1Q_3Q_4Q_5+Q_1Q_2(R_3Q_4Q_5+Q_3P_4)$;
   $A_6=Q_1Q_2Q_3Q_4Q_5$
6. $H = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$
7. $A=[HA_1\ HA_2\ HA_3\ HA_4\ HA_5\ HA_6]$;
8. A=[0.312 0.159 0.427 0.482 -0.323 0.205 0.290 0.126 0.081-0.422 -0.080 0.158 0.158 0.080 -0.422 -0.081 0.126 -0.290 0.205 0.323 0.482 -0.427 0.159 -0.312].

The low-pass and high-pass filters are at the first and second rows of matrix A, respectively.

3. Experiment

As shown in Tables 1, three different type yarns (ringspun, open-end, and high-draft) are employed for this research. Ten replications of three kinds of yarns were prepared for this study. The samples with count of 6/1 - 28/1 and CV% of 15-20 are mechanically conditioned at the room temperature for a month. The yarn samples were conditioned under standard atmosphere for a weak prior to testing. From each package, a total of 1000 m was measured continuously at a constant speed of 200 m/min and saved into data files after converting them to digital signals. The sampling rate of the data acquisition system was 833 KHz corresponding to measurement of the diameter at every 2mm segment of yarns. The density profiles of yarns used have been shown in Figure 1.

Table 1. Test materials

Sample	Type	Count	Test Machine
ringspun	Cotton/ringspun	17/1	Zweigle
openend	Cotton/openend	28/1	Zweigle
high-draft	Cotton/high-draft	20/1	Zweigle

4. Results and Discussions

In this section, the filter coefficients were generated in order to satisfy a specific criterion, adaptable to various spinning conditions. Based on the algorithm developed in Section 2, a set of optimal filter coefficients were generated for both ringspun and openend yarns. The coefficients minimizing the sum of squared errors between original and reconstructed signals at a given compression ratio have been chosen as a set of optimal filter coefficients. For obtaining the optimal filter coefficients, an optimization method based on a quasi-Newton method was employed. The method incorporates a mixed quadratic and cubic line search algorithms[9]. Some empirical and heuristic rules were also combined for determining the values *m, k* and *j* (See Section 2).

While the values *m* and *k* have been arbitrarily chosen by considering the processing time and compression performance, the value *j* has been fixed at 10. Any value of *j* greater than 10 was considered unnecessary as the magnitudes as well as the number of the wavelet coefficients become small at the lower frequency scale windows.

Following these guidelines, a set of optimal wavelet filters were produced for ringspun and

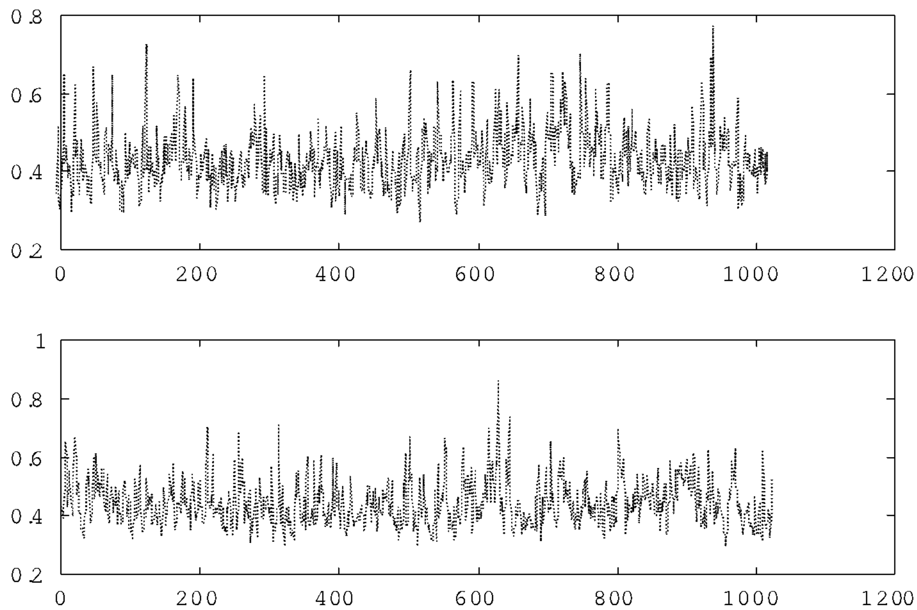

Fig. 1. Density profiles of tested yarns.

openend yarns. For the ringspun yarn samples, the filter length n and the number of band m were 12 and 2, respectively. The following is a set of filter coefficients for the ringspun yarn sample. The coefficients, round off to one thousandth decimal point, are as follows:

g : {0.016, -0.041, -0.067, 0.386, 0.813, 0.417, -0.076, -0.059, 0.023, 0.006, -0.002, -0.001}

h : { -0.001, 0.002, 0.006, -0.023, -0.059, 0.076, 0.417, -0.813, 0.386, 0.067, -0.041, -0.016}

Using the process dependent basis constructed, compression experiments have been performed on the yarn density signals during monitoring. The main procedure is as follows:

1. Construct a process dependent basis.
2. Perform a wavelet packet transform.
3. Apply the "best basis" selection algorithm based on entropy criteria.
4. Reconstruct a signal from the reduced wavelet coefficients.

Finally, original and reconstructed signals have been compared for displaying the compression errors in Figure 2. As shown in the figure, two signals are very similar to each other in appearance.

Figure 3 compares the performance of two bases when applied to a ringspun yarn density.

Compared to a Daubechies-5 wavelet, the process dependent basis shows a considerable reduction in the sum of the squared reconstruction error.

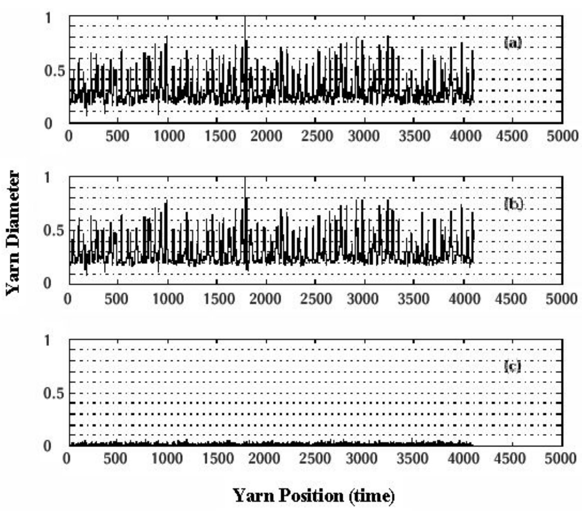

Fig. 2. Comparison of the original (a) and the 95% (b) compressed signals and the differences((c) = (a) − (b)).

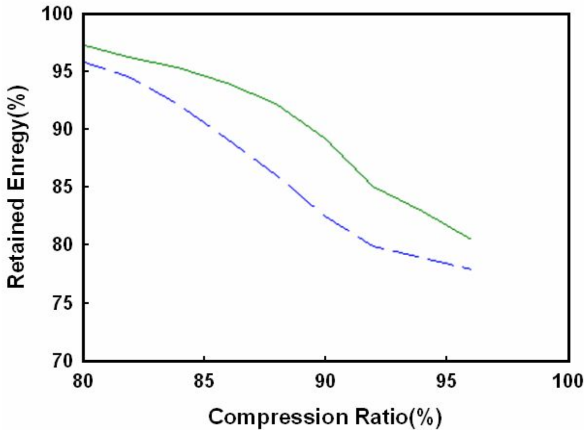

Fig. 3. Comparison of the compression performances of two bases(− −: a Daubechies-5 and −−:a process dependent basis).

5. Conclusions

A data reduction algorithm was developed in order to store a large amount of yarn diameter signals by a newly developed wavelet compression method. The process dependent basis(wavelet) developed outperformed the conventional wavelets by being optimized to a specific signal. Compared to the conventional wavelets, the process dependent basis could achieve a relatively higher level of compression. It was shown that the yarn signals could be compressed by over 95% without a significant loss of information.

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