

웨이블릿-몬테 카를로법을 이용한 가상 직물이미지의 모사

Wavelet-Monte Carlo Simulation for Virtual Fabric Imaging

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Abstract : The algorithm developed in this paper allows us to generate or synthesize a large amount of data sets using only a small amount of signal features obtained from the original data set. Because the simulated density profiles of yarns retain the original features without a significant loss of information on the location of imperfections, the resulting fabric images are likely to resemble the original images. The data expansion system developed could generate a large area of fabric images by combining the Monte Carlo simulation and the wavelet sub-band exchange algorithm developed. The system has proven effective for simulating realistic fabric images by retaining the location of imperfections such as neps, thin and thick places.

Key words : wavelet, Monte-carlo simulation, fabric imaging, data synthesis, sub-band exchange

요약 : 제한된 방적사의 두께신호로부터 유사구조를 갖는 다량의 데이터를 합성하는 방법이 개발되었다. 모사된 방적사의 두께신호는 넵 등의 발생횟수는 물론 발생위치에 관한 정보를 원래의 데이터와 유사하게 포함하고 있으므로, 이를 통해 모사한 직물이미지의 외관도 원래의 것과 크게 다르지 않은 특징을 가지고 있다. 몬테 카를로 모사법과 웨이블릿 변환을 결합한 알고리즘을 결합하여 개발된 방법은 넵, 두꺼운 부분, 가는 부분 등 방적사 외관상의 특징을 나타내는 요소들을 그대로 유지함으로써, 가상의 직물이미지를 모사하는 데 매우 효과적인 방법을 제공한다.

주제어 : 웨이블릿, 몬테 카를로 모사법, 직물이미지, 데이터 합성, 서브밴드 교환법

1. Introduction

The existing measures such as CV%, U%,

spectrogram and others have not been useful for expressing the visual qualities of yarn and fabrics directly [1,2]. In 1994, a new yarn uniformity

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measure, therefore, was developed by Jeong in order to simulate the visual perception on qualities of yarn and fabrics using the density profiles of yarns [3]. It was shown that the density profiles of yarns captured from the spinning process could be used for visualizing fabric qualities.

In spite of its simplicity and excellent visual effects, the fabric visualization system has several limitations. First of all, the system is heavily dependent on the length of yarns measured [4]. In view of the fact that the area of actual fabrics is much larger than that of the fabric images produced from a limited amount of yarn data, the process of visualization by a direct mapping of the limited yarn data would likely to lead false or inconsistent fabric images.

Since a yarn sample of 400m long can generate only 0.2m^2 of fabric image, it is important to develop a reliable algorithm capable of retaining the original feature of a given yarn but regenerating a sufficient length of yarn for visualizing fabric images. The algorithm developed in this paper allows us to generate or synthesize a large amount of data sets using only a small amount of signal features obtained from the original data set. Because the reduced density profiles of yarns retain the original features without a significant loss of information on the location of imperfections, the resulting fabric images are likely to resemble the original images.

2. Signal Synthesis from the Reduced Data Sets

Two methods were developed in order to

generate a large amount of simulated yarn signals from a limited amount of signals reduced from the original data. In performing the specific task, a feature extraction algorithm based on analysis of wavelet energy distribution was developed by wavelet packet transform. In addition, stochastic simulations based on the Monte Carlo method will be employed for providing unpredictable short-term defects. These techniques will be used for predicting the fabric qualities by generating a large area of fabric image.

2.1 Data Synthesis Using the Sub-band Exchange Algorithm

There are two essential methods for discarding wavelet coefficients : hard and soft thresholdings [5]. By thresholding, only wavelet coefficients whose absolute values exceed ϵ_j for each level j are retained. The algorithm can be applied for the energy of each bin instead of individual coefficients without loss of generality. Thus, thresholding replaces $b(j,k)$ by $\tau_j(j,k)$ where the function τ_j is defined by

$$\tau_j(x) = \begin{cases} x, & |x| \geq \epsilon_j \\ 0, & |x| < \epsilon_j. \end{cases} \quad (1)$$

This algorithm of retaining x values is called "hard thresholding". On the other hand, soft thresholding would replace τ_j is defined by the Lipschitz continuous function

$$\tau_j^o(x) = \begin{cases} x, & |x| \geq \epsilon_j \\ 2(|x| - \epsilon_j / 2) \text{sgn } x, & \epsilon_j / 2 \leq |x| < \epsilon_j. \\ 0, & |x| < \epsilon_j / 2 \end{cases} \quad (2)$$

Only the coefficients remaining after the

thresholding will be used for the sub-band exchange algorithm. Once the principal bins are selected, we can apply the sub-band exchange algorithm. The algorithm can be used within single sub-block as well as among multiple sub-blocks. Shown in the following are the algorithm and the steps involved for generating a large amount of simulated data from a limited amount of actual data.

Algorithm 2.1

(The Subband Exchange Algorithm)

Given a sequence consisting of S sub-blocks, [6]

Step 1 : Construct a dictionary of orthonormal bases \mathbf{g} (i.e. adaptive bases optimized for a specific process)

Step 2 : Construct time-frequency maps Γ_n for $n = 1, \dots, N$

Step 3 : Set $\Gamma(j, k) = T(j, k)$ and τ^0 for $k = 0, \dots, 2^j - 1$

Step 4 : Determine the subspace $T(j, k)$ for $j = J-1, \dots, 0, k = 0, \dots, 2^j - 1$ by the following rule:

Set $\tau^0(x)$ to a predetermined value.
 If $\Gamma(j, k) \geq \tau^0(k)$,
 then $\Gamma(j, k) = T(j, k)$,
 else $\Gamma(j, k) = 0$.

Step 5 : $F(j, k) = |T(j, k)|$

Step 6 : Rearrange $F(j, k)$ in a random order

As the sub-signals are ordered according to the frequency resolution, they should be exchanged in a same frequency band. Since the exchange has been performed between sub-signals at same scale (frequency), the total number of wavelet

packet coefficients is not changed after the exchange. Only the amount of energy at a specific bin is altered by a random rearrangement of the wavelet packet coefficients.

2.2 Data Synthesis Using Stochastic Simulations

Stochastic models for the yarn density profiles developed could be used for data expansion [2]. The models used were Poisson for the occurrence of thick place, a gamma probability distribution for the length of thick place and a generalized Pareto distribution for amplitude of the thick places. Once the parameters of the model are obtained, a large amount of sample paths can be produced by generating the random numbers following the models.

For a Poisson process, the inter-arrival times of neps/thick places, B , follow an exponential distribution [7].

$$F(k) = 1 - e^{-\lambda k} = y \quad (3)$$

A random sample has to be obtained from the distribution for representing the time to the occurrence of the neps/thick places. The procedure is performed by obtaining the inverse of Equation (3) and substituting the estimate value of λ , $\hat{\lambda}$

$$k = -\frac{1}{\hat{\lambda}} \log(1 - y) = F^{-1}(y) \quad (4)$$

$$k = \frac{-\log\{1 - F(k)\}}{\hat{\lambda}} \quad (5)$$

A random variable distributed uniformly on the interval 0 to 1, $U(0,1)$, is substituted for $F(k)$ and with a given yarn density profile, the value k is obtained as follows.

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$$k = F^{-1}(U) = -\frac{1}{\lambda} \log(1 - U) \quad (6)$$

As $1-U(0,1)$ is also a uniformly distributed random number on the interval $(0,1)$, a more computationally efficient form of Equation (6) is

$$k = \frac{-\log\{U(0, 1)\}}{\lambda} \quad (7)$$

which can be used to obtain random values of inter-arrival times between thick places, B , the time from the start of a thick place to the start of a subsequent thick place. The related value, B^* , the time from the end of a thick place to the start of a subsequent thick place, is also exponentially distributed. If λ^* is denoted as the parameter of this distribution, then, it can be written,

$$(\lambda^*)^{-1} = (\lambda)^{-1} - E(L_i) \quad (8)$$

where $E(L_i)$ is the expected value of the length of thick places. By using $E(L_i) = \alpha/\beta$, we obtain final form of the value B^* as follows.

$$(\lambda^*)^{-1} = (\lambda)^{-1} - \alpha/\beta \quad (9)$$

The length of thick places, L , follows a gamma distribution.

$$f(L | \alpha, \beta) = \frac{1}{\Gamma(\alpha)\beta^\alpha} L^{\alpha-1} e^{-L/\beta}, (L > 0), \quad (10)$$

$$(L \leq 0) \alpha, \beta > 0$$

Thus, an equation can be used to obtain random samples from the distribution of length of thick places.

$$L = -\hat{\beta} \log\{U(0, 1)\} \quad (11)$$

where $\hat{\beta}$ is the estimated value of β .

The extreme value distribution can be used for simulating a sequence of amplitudes of diameter values in neps/thick places.

Algorithm 2.2(The Stochastic Data Synthesis Algorithm).

Step 0 : Generate background of a signal using random numbers

Step 1 : Compute the value of inter-arrival time using Equation (7) and a set of parameters λ_1, λ_2 estimated along the yarn length

Step 2 : Compute the value of the length of thick places using the parameters α, β estimated

Step 3 : Compute the values of the amplitudes in thick places using the parameters k, σ estimated

Step 4 : Repeat steps 0-3 for the desired length of yarns

Figure 2 shows a profile of a signal generated by the stochastic models using Algorithm 2.2. The signal was generated sequentially in an order of 1) background of a signal, 2) inter-arrival time for neps/thick places, 3) length of the thick places and 4) the amplitudes of the diameter values in neps/thick places.

3. Results and Discussions

Limitation in areas of fabric images produced by yarn signals has been considered to be a main drawback in applying the fabric visualization system to prediction of fabric appearance. In this section, a comparison has been made between fabric images produced by a original yarn of 400m lengths and a 400m long simulated yarn based on data set reduced from 1,000m length of

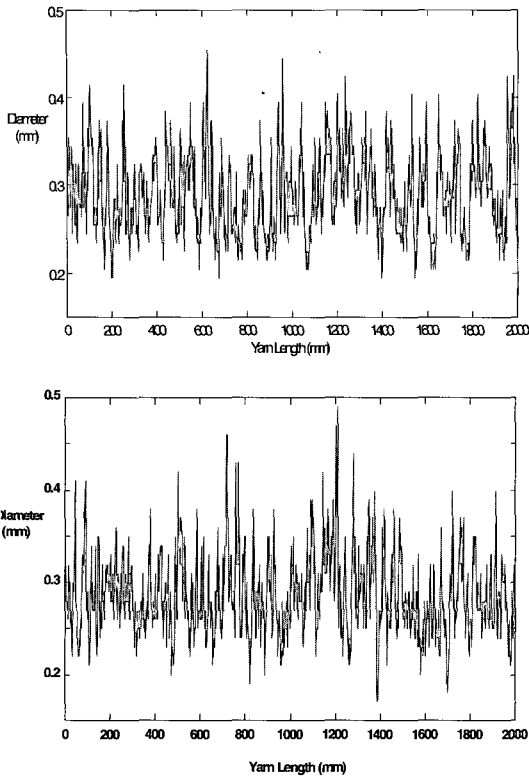


Figure 1. Comparison of an actual and a simulated signal

(Top : An actual signal, Bottom : an signal generated by the stochastic models of $\lambda_1=20$, $\lambda_2=20$, $\alpha=3.0$, $\beta=0.9$, $k=0.2$, and $\sigma=1.2$)

an actual yarn. The simulation was made by combining the two methods, the sub-band exchange and the stochastic simulation. While the sub-band exchange algorithm was used for generating background signals, the stochastic simulation was employed mainly for various defects such as neps and thick places.

Figures 2 and 3 show woven fabric images generated from the actual yarn signal and the simulated yarn signals. The fabric image simulations using other simulated yarn signals have revealed that the fabric images were similar to the images of the original real fabrics in appearance.

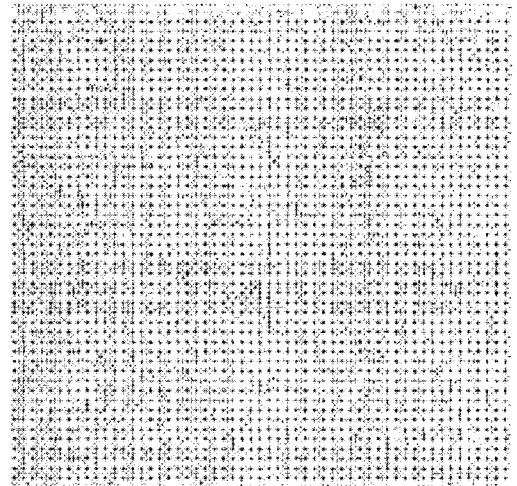


Figure 2. A fabric image produced from the actual yarn signals

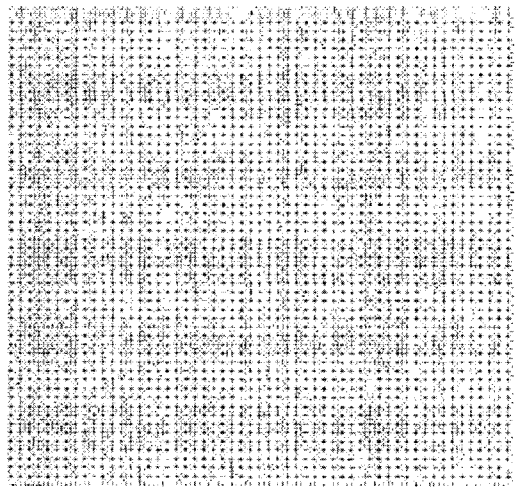


Figure 3. A fabric image produced from the simulated yarn signals

4. Conclusions

Explored in this paper feasibility of applying a wavelet packet based sub-band exchange algorithm and a stochastic simulation for data expansion and fabric simulation. The conventional spectrogram analysis could not reveal characteristics of yarn density profiles, only detecting the periodic faults. As a result, data

expansion method using Fourier-based time domain (time-series analysis) and frequency domain (spectrogram) approaches cannot provide an optimal solution for yarn and fabric quality analyses and visualization. On the other hand, the sub-band exchange algorithm developed here was found to provide more realistic fabric images quite effectively. The new method provides an efficient data expansion algorithm for generating a large area of fabric image. Using the wavelet-stochastic simulation method developed, we can a large number of yarn density profiles from limited data for either control purposes or graphical representation of the visual qualities of the yarns and the resulting fabrics. The method will be incorporated into the simultaneous yarn measurement system under development for future on-line quality control of spun-yarn production. As a final product, a standalone yarn quality measurement /characterization system can be envisioned.

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