Decoupling basis-weight measurements in paper manufacture

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Abstract

The online measurement of basis weight in paper production is hampered by excessive noise, and the zig-zagging motion of the scanner transversing the sheet. Decoupling variations in the direction of production form variations across the sheet and visa-versa. An algorithm is presented that attempts to reconstruct this two-dimensional data from the single scanner.

1 Introduction

In the production of paper, the control of key quality parameters is needed in both the cross direction (CD) and in the machine direction (MD) of the finished sheet. However the values are measured by a single radioactive sensor sweeping laterally across the rapidly moving sheet resulting in a zig-zag path as shown in Fig. 1 which illustrates a basis weight map of a 80×2 meter paper strip measured offline by [2]. Superimposed is the scanner path with the resultant as-measured data.

In order to obtain both the machine and cross-machine profiles of the sheet, one needs to decouple these measurements obtained from the sensor. Simply averaging individual measurements across one sweep is inefficient since we then obtain only one averaged reading per sweep and additionally the resulting CD profile will include unwanted MD variations.

Based on the assumptions that the CD profile variations are slower than the MD profile variations and that MD variations do not effect the CD profile, Dumont and co-workers, [4, 5] and various vendors, [1, 3], estimated MD and CD profiles using state estimation, adaptive or even wavelet techniques. This leads to an improved bandwidth, at least for the MD control of the paper machine. This document describes one such approach which is currently implemented on a 5-layer board machine at Skoghall, Sweden as part of an ongoing optimal control project described in [6].

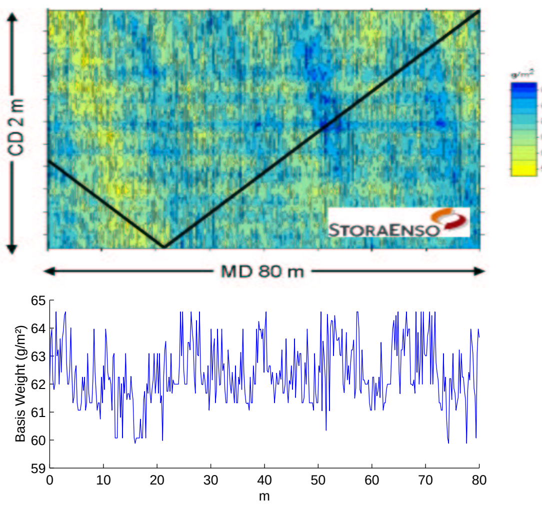


Figure 1: Upper: A basis weight map of a paper sheet and resultant scanner signal in g/m^2. Data provided by Stora Enso, [2].

2 Machine direction estimation

As the sensor sweeps back and forth across the sheet it delivers a measurement $z(s, n)$ at scan s and CD position n as shown in Fig. 2. At the kth sampling interval, we batch a number of previous raw measurements and form the auxiliary measurement,

$$\mathbf{z}(k) \stackrel{\Delta}{=} [z(s,n),\ z(s,n-1),\ z(s,n-2),\ \cdots \quad z(s,n-m)]^T \tag{1}$$

Using $\mathbf{z}(k)$ and an estimate of the CD profile, $\mathbf{x}_\mathrm{c}(k)$, obtained from the CD estimation algorithm described in section 3 for the corresponding section of the sheet, we can decompose the measurement into an MD component, $z_\mathrm{m}(k)$,

$$z_\mathrm{m}(k) = \mathrm{mean}(\mathbf{z}(k) - \mathbf{x}_\mathrm{c}(k)) \tag{2}$$

and subsequently update the full-width mean of the sheet, $x_\mathrm{m}(k+1)$ using a Kalman filter.

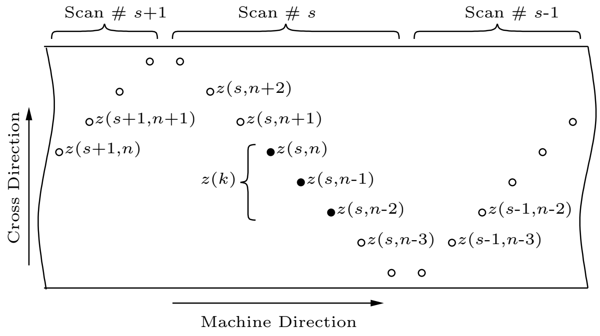


Figure 2: Sampling the sheet using a single scanning sensor

3 Cross-machine estimation

To estimate the zero-mean CD profile of the sheet we use the value of the full-width mean of the sheet $x_{\rm m}(k+1)$ calculated in section 2. However as the MD estimation algorithm is designed with the assumption that the CD profile stays constant for long periods of time, we need to fully decouple the CD estimation algorithm from the MD estimation algorithm again estimating the MD profile.

Given the measurement, $\mathbf{z}(k)$, we extract the CD component

$$\mathbf{z}_{\rm c}(k) = \mathbf{z}(k) - x_{\rm mcd}(k) \tag{3}$$

combined with the zero-mean CD profile, $\mathbf{x}_{\rm c}$, of the corresponding section of the full CD profile is updated using an exponential filter with a variable forgetting factor,

$$\mathbf{x}_{\rm c}(k+1) = \mathbf{K}\mathbf{x}_{\rm c}(k) + (\mathbf{I} - \mathbf{K})\left(\mathbf{z}_{\rm c}(k) - \mathbf{x}_{\rm c}(k)\right) \tag{4}$$

The time-varying gain $\mathbf{K}(k)$ in Eqn. 4 is an ad-hoc forgetting factor that is calculated online using,

$$\mathbf{K}(k) = (\lambda_{\max} - \lambda_{\min})\,\mathrm{diag}\left(\begin{bmatrix} \mathrm{e}^{-d(n)/(2T)} \\ \mathrm{e}^{-d(n-1)/(2T)} \\ \vdots \\ \mathrm{e}^{-d(n-m)/(2T)} \end{bmatrix}\right) + \lambda_{\min} \tag{5}$$

where $\lambda_{\max}, \lambda_{\min}$ are the maximum and minimum update gains, T is the time it takes the scanner to move from one end of the sheet to the other and $d(n)$ is the time elapsed since the same section of the sheet was previously measured.

When the zero-mean CD profile estimate has been updated we remove the bias (so that the CD profile is zero mean) using,

$$\mathbf{x}_{\rm c}(s+1) = \mathbf{x}_{\rm c}(s+1) - \underbrace{\mathrm{mean}(\mathbf{x}_{\rm c}(s+1))}_{\text{bias}} \tag{6}$$

The bias is also used to update the CD-algorithm estimate of the full-width mean,

$$x_{\rm mcd}(k+1) = x_{\rm mcd}(k) + \mathrm{mean}(\mathbf{x}_{\rm c}(s+1)) \tag{7}$$

In summary, the estimation algorithm consists of the following steps:

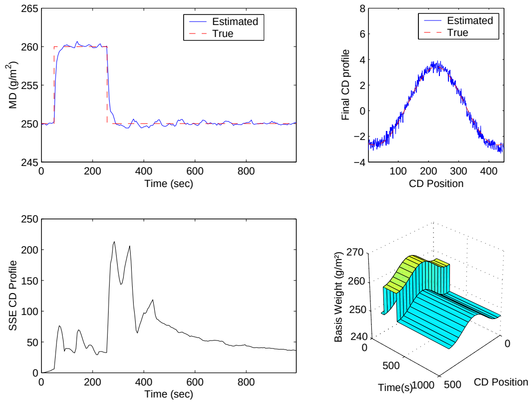
1. MD Algorithm
   (a) Batch raw measurements and form $\mathbf{z}(k)$ from Eqn. 1.
   (b) Calculate the MD average, $z_{\rm m}(k)$ from Eqn. 2 where $\mathbf{x}_{\rm c}(k)$ is the predicted CD profile for the section of the CD profile that is covered in $\mathbf{z}(k)$ given in the previous iteration in step 2b.
   (c) Update the MD estimate using perhaps a simple state estimator of the form $x_{\rm m}(k+1) = x_{\rm m}(k) + K_1\left(z_{\rm m}(k) - x_{\rm m}(k)\right)$
2. CD algorithm
   (a) Calculate the CD component, $\mathbf{z}_{\rm c}(k)$, using Eqn. 3.
   (b) Update the corresponding section of the CD profile, $\mathbf{x}_{\rm c}(k+1)$, using the exponential filter, defined by Eqn. 4.
   (c) Subtract the bias from the full-width CD profile $\mathbf{x}_{\rm c}(s+1)$ using Eqn. 6.
   (d) Update the full-width mean CD estimate using Eqn. 7.
3. Wait for the next sample and return to step 1.

4 Simulated basis weight tests in MD and CD

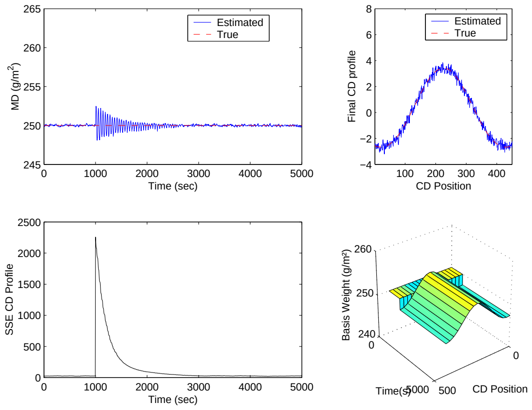
Prior to implementing this estimator on an actual machine, we needed to investigate the response to step changes in MD and CD profiles. Notwithstanding that we assumed the CD profile is essentially constant in section 2, we still need to see how fast the estimation algorithm converges to a new profile and the resultant effect on the MD profile estimate. Our target paperboard machine uses a scanner with 450 data boxes and travel time of 45s with a sample time of 5s meaning that 50 samples are collected when forming $\mathbf{z}(k)$.

The upper left trend in Fig. 3(a) demonstrates that the estimated MD profile (solid) follows the actual profile (dotted) of a sheet with two MD steps, despite being fed a measurement corrupted with noise of standard deviation 1 g/m^2. An exaggerated three-dimensional view of the noise-free paper weight profile is given in the bottom right Fig. .

The upper right Fig. shows that the estimated CD profile eventually converges to the true CD profile, but the lower left trend shows that the CD profile estimate was disturbed by the step change in the MD profile where the squared sum of the errors between the true



(a) The performance of the estimation algorithm when subjected to two step changes in MD profile.



(b) The performance of the estimation algorithm when subjected to a step change in CD profile.

Figure 3: Machine direction and cross-machine direction step tests

CD profile and the estimated CD profile is shown at each sampling instance. Note however the reverse is not true; the disturbance of the estimated CD profile caused only minor corresponding disturbances of the MD profile estimate.

Fig. 3(b) shows the result of the estimation procedure to a step change in CD profile (in the same format as Fig. 3(a)). Measurement noise was again added to the test sheet (lower right figure) with a standard deviation of 1 g/m^2. The convergence rate of the CD profile estimate is now slower than the convergence rate for the MD profile estimate, as expected. Furthermore we see errors in MD estimate stemming from the poor CD profile estimate. As soon as the CD profile estimate converges to the true CD profile, the disturbance of the MD profile estimate disappears.

5 Conclusion

Actual variations in a paper sheet, such as those shown in Fig. 1, are not just restricted to machine or cross-machine directions. Therefore to extract this 2D signal from a scanner moving along a zig-zag path requires some sophistication and smoothing. The algorithm presented converged to the true basis-weight profile for steps in both machine and cross machine cases. While variations in the MD direction had little effect on the estimated CD value, the reverse is not true. But if we assume that the CD profile changes only gradually, implying that all fast variations are variations in the MD profile, then the overall performance of this algorithm is adequate. However one potential problem is that if the process is noisy, then disturbances caused by errors in the CD profile could be a problem for the MD control of the basis weight.

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