Développement d’un système d’imagerie spectrale pour contrôle de la qualité en-ligne des procédés d’extrusions de composites plastiques

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Several products are made of multi-component particulate mixtures, solidified composite melts, etc

- Polymer processing
- Pharmaceutical
- Mineral and metallurgical processes, etc.

Quality depends upon:
- Overall composition
- Size and spatial distribution of the components within the product
- Physical state (i.e. level of crystallinity)
- Surface aesthetics, etc.

Raw materials available from new suppliers, greater variability → need more frequent measurements and closer monitoring & control
In the laboratory: analytical instruments (DSC, TGA, XRD, etc), devices for testing mechanical properties, etc.

- Cost/labor intensive, long time delays
- Destructive
- Small samples
- Often cover < 1% of incoming raw materials or production
- Rapid and non-destructive tools for testing quality

→ Machine vision for estimating/monitoring product quality
Quality Control of Extruded Wood-Plastic Composites

Quality attributes:
- Dispersion of key components
- Mechanical properties
- Surface aesthetics

Recipe (% wood fibers)
Throughput
Screw Speed
Barrel temperature

Twin-screw extruder
HDPE resin
Wood fibers

Quality control system

VIS-NIR (400-1700 nm)
Line-scan spectral imaging system
Multivariate VIS-NIR imaging

NIR and visible cameras and spectrometers

illuminated plane

Cross direction $x$

Machine direction

Single line-scan image on the camera CCD

Spatial axis ($x$)

Spectral axis ($\lambda$)

Spectrum of a single spatial point $(x,y)$

Intensity

Spectral axis ($\lambda$)

Spectral axis

$\lambda$

Cross direction

Machine direction

$y$
Experimental

- DOE on machine variables and recipe \((2^3 + 3)\)
- 12 steady-states & transitions
- Spectral VIS-NIR images were collected every about 30 cm
- Samples were taken near imaged regions for mechanical testing (traction along MD) in 5 replicates
  - 6 points along stress/strain curves + enthalpy of fusion \((\propto \text{crystallinity})\)
Methodology

**Image acquisition**

(pixels CD x scans MD x λ) = (25 × 25 × 500)

**Pretreatment**

Wavelength Selection → (25 × 25 × 6)

[Gosselin et al. (2010), Chemom Intell Lab Syst 100:12–21]

**Feature extraction**

Spectral signatures (2-D mean intensity at each waveband)

Textural features (spatial organization – GLCM)

**Analysis / classification / regression**

**Desired information**

Images / samples

\[ X_F \]

N 6 6+12=18 7

Spectral features Textural features Product properties

PLS
Quality space has 2 main variance directions

- 6 relevant spectral bands were identified and selected
  - Light intensities were averaged within each band (6 spectral features)

- 12 textural features: entropy and correlation of GLCM [32 GL, L= 2,5,10 pixels, cross and machine directions] on image @ band 1210-1260 nm
Data collected during steady-state operation used for training the model (11 states × 25 line scans)

Latent Variable Model (PLS)

\[ X = T P^T + E \]
\[ Y = T Q^T + F \]
\[ T = X W^* \]

Validation using data collected during transients (6750 line scans)
WPC Quality in Steady-State

Product appearance (color-texture) / wood content
WPC Quality in Transitions

(A) Scatter plot with labeled points indicating steady states, transition 5 to 6, and transition 9 to 10.

(B) Line graph showing Hotelling's T based on 9 and 5 over time (min).
WPC Quality in Transitions

Table 2. PLS model ability in training ($R_{Y,train}^2$) and validation ($Q_{Y,train}^2$).

<table>
<thead>
<tr>
<th>Property</th>
<th>Training set ($R_{Y,train}^2$)</th>
<th>Validation set ($Q_{Y,train}^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enthalpy of fusion</td>
<td>0.853</td>
<td>0.851</td>
</tr>
<tr>
<td>Modulus</td>
<td>0.884</td>
<td>0.880</td>
</tr>
<tr>
<td>Stress at yield</td>
<td>0.893</td>
<td>0.869</td>
</tr>
<tr>
<td>Strain at yield</td>
<td>0.891</td>
<td>0.870</td>
</tr>
<tr>
<td>Stress at break</td>
<td>0.870</td>
<td>0.818</td>
</tr>
<tr>
<td>Strain at break</td>
<td>0.880</td>
<td>0.809</td>
</tr>
<tr>
<td>Energy</td>
<td>0.912</td>
<td>0.890</td>
</tr>
<tr>
<td>Overall</td>
<td>0.883</td>
<td>0.855</td>
</tr>
</tbody>
</table>
Conclusions and future work

- Very promising results for a simple composite system (1 filler, 1 polymer specie)
- Grant from Quebec Research Consortium for Polymer Processing and Composites (CRPCQ) + 2 companies for extending the work to commercial products (5-10 components)
- Use of recycled polymers (post-industrial/consumer) instead of fresh resins
- Demonstrate closed loop quality control at pilot plant scale
Acknowledgments

- Ryan Gosselin now prof. at Université de Sherbrooke
- Prof. Denis Rodrigue (polymer processing)
- NSERC funding
- CFI (spectral imaging systems)
QUESTIONS ?
LOOP

Laboratoire d’observation et d’optimisation des procédés
Imagerie hyper-spectrale UV-VIS-NIR

NIR: 900-1700 nm
VIS: 400-900 nm
UV: 200-400 nm

sample
Multivariate Imaging

- Images containing several spectral channels
  - Gray level images → 1 channel (matrix)
  - Color RGB images → 3 channels (array or cube)
  - Multi-, Hyper-spectral images → 5 – 1000 channels

- Choice depends upon the complexity of the image features to be extracted
  - Bar code vs map of chemical components on a surface

- Strong collinearity between the light intensities of adjacent channels (wavelengths) measured for each pixel of the image

- Multivariate Statistical Methods (PCA/PLS) are typically used for analyzing these images
Mechanical Testing

- Typical stress-strain curve for LDPE/PS film with the parameters studied: Young’s modulus (1), the strength and associated strain (2 and 3), the stress and strain at rupture (4 and 5) as well as the sample toughness (6).
Mechanical Testing

PCA Y

- modulus
- stress at yield
- stress at break
- enthalpy
- energy
- strain at yield
- strain at break

$p_1$ vs $p_2$
PLS Model Interpretation

A

Stress at yield and break
Strain at yield and break
Energy
Enthalpy

B

VIP (-)

Entropy 2 MD
Entropy 5 TD
Entropy 5 MD
Entropy 2 MD
Entropy 10 MD
Entropy 2 TD
Entropy 10 TD
Correlation 10 MD
Correlation 2 MD
Correlation 5 MD
2nd wavelength
3rd wavelength
4th wavelength
5th wavelength
6th wavelength
1st wavelength

Properties
Spectra
Entropy
Correlation
Table 1. Randomized $2^3$ full factorial design for machine variables at 20% wood (samples 1-8) combined with 3 additional experiments in which wood content was varied under nominal processing conditions (samples 9-11).

<table>
<thead>
<tr>
<th>Sample</th>
<th>Wood (%)</th>
<th>Temperature (°C)</th>
<th>Throughput (g/min)</th>
<th>Screw Speed (rpm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20</td>
<td>160</td>
<td>600</td>
<td>70</td>
</tr>
<tr>
<td>2</td>
<td>20</td>
<td>160</td>
<td>500</td>
<td>90</td>
</tr>
<tr>
<td>3</td>
<td>20</td>
<td>180</td>
<td>500</td>
<td>70</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>180</td>
<td>600</td>
<td>90</td>
</tr>
<tr>
<td>5</td>
<td>20</td>
<td>160</td>
<td>600</td>
<td>90</td>
</tr>
<tr>
<td>6</td>
<td>20</td>
<td>160</td>
<td>500</td>
<td>70</td>
</tr>
<tr>
<td>7</td>
<td>20</td>
<td>180</td>
<td>600</td>
<td>70</td>
</tr>
<tr>
<td>8</td>
<td>20</td>
<td>180</td>
<td>500</td>
<td>90</td>
</tr>
<tr>
<td>9</td>
<td>10</td>
<td>170</td>
<td>550</td>
<td>80</td>
</tr>
<tr>
<td>10</td>
<td>20</td>
<td>170</td>
<td>550</td>
<td>80</td>
</tr>
<tr>
<td>11</td>
<td>30</td>
<td>170</td>
<td>550</td>
<td>80</td>
</tr>
</tbody>
</table>
Dynamics between process variations and PLS scores

Table 3. First order dynamic time constants and delays. Confidence intervals are indicated between parentheses.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Time constant</th>
<th>Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$T_p$ (min)</td>
<td>$T_d$ (min)</td>
</tr>
<tr>
<td>Temperature (°C)</td>
<td>6.55 (1.78)</td>
<td>5.58 (2.48)</td>
</tr>
<tr>
<td>Throughput (g/h)</td>
<td>3.75 (1.04)</td>
<td>2.61 (0.77)</td>
</tr>
<tr>
<td>Screw speed (rpm)</td>
<td>3.92 (1.46)</td>
<td>1.70 (1.56)</td>
</tr>
<tr>
<td>Wood content (%)</td>
<td>4.31 (0.33)</td>
<td>3.62 (0.22)</td>
</tr>
</tbody>
</table>
Nature of Data & Problem formulation

**Images / samples**

- Image features
- Process data (instrumentation)
- Latent variables (score vectors)
- Classes / key process variable

**Mathematical Formulations**

**PCA:** \[ X = T P^T + E \]

**PLS:** \[ X = T P^T + E \]
\[ Y = T Q^T + F \]
\[ T = X W^* \]
N = 6
6+12 = 18

**Spectral features**

**Textural features**

**Product properties**

**Images / samples**

**PLS**

$$X = TP^T + E$$

$$Y = TQ^T + F$$

$$T = XW^*$$

**PCA**

$$X = TP^T + E$$
Multi-Resolution GLCM Texture Analysis

- Grey Level Co-occurrence Matrix (GLCM)
  - Tabulation of how frequently different combinations of pixel brightness values (grey levels) occur in an image
  - Computed for pairs of pixels at a distance L and angle $\angle$ for each other

- Scalar texture descriptors: energy, entropy, correlation, etc. (Haralick’s features) computed from GLCM

\[
\text{entropy} = -\sum_{i,j} p_{i,j} \log(p_{i,j})
\]

\[
\text{correlation} = \sum_{i,j} \frac{ijp_{i,j} - \mu_i \mu_j}{\sigma_i \sigma_j}
\]
Digital Images

Multivariate Image

Multivariate Image

Spatial axis \((x)\)

Spectral axis \((\lambda)\)

\(\lambda_1\)

\(\lambda_2\)

\(\lambda_3\)

\(\lambda_k\)

200nm 380nm 900nm 1700nm 8-15µm

UV Visible IR

200nm 380nm 900nm 1700nm 8-15µm
Analyse de texture par ondelettes (WTA)

\( f(x) \)

\[ \psi_{m,n}(x) = 2^{-m/2} \psi(2^{-m} x - n) \]

\[ c_{m,n} = \int_{\mathbb{R}} f(x) \psi_{m,n}(x) \, dx = \langle \psi_{m,n}, f \rangle \]

\[ \phi_{j,\ell}(k) = 2^{j/2} h_0(k - 2^j \ell) \quad h_0 = \text{Filtre passe bas} \]

\[ \psi_{j,\ell}(k) = 2^{j/2} h_1(k - 2^j \ell) \quad h_1 = \text{Filtre passe haut} \]

DWT

\[ a_{j,\ell} = \langle f(k), \phi_{j,\ell}(k) \rangle \quad \text{et} \quad d_{j,\ell} = \langle f(k), \psi_{j,\ell}(k) \rangle \]
Analyse de texture par ondelettes (WTA)

$H_0 = \text{Filtre passe bas}$

$H_1 = \text{Filtre passe haut}$
Analyse de texture par ondelettes (WTA)
Multivariate Image Analysis

Reorganization

\[
X = \begin{bmatrix}
    t_1 \times p_1^T \\
    t_2 \times p_2^T \\
    E
\end{bmatrix}
\]

\[
\begin{align*}
T_1 \otimes p_1 & \quad 3 \times 1 \\
T_2 \otimes p_2 & \quad 3 \times 1 \\
E & \quad 3
\end{align*}
\]