Colour Management for 3D printer

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Overview

- Introduction
- Pilot work
  - Colour characterisation for 3D printer
  - Spectral characterisation for 3D printer
- Discussion and conclusion
- Conclusion
- Future work
Colour management

- Reproducing colours accurately and consistently
- Colour transformation between device-dependent and device-independent colour space
Forward colour characterisation

CMYK to CIELAB:

Reverse colour characterisation

CIELAB to CMYK:
For 2D printers

Colour characterisation methods:
• Least square polynomial fitting
• 3D Lookup tables interpolation
• Artificial neural network

Spectral characterisation methods:
• Least square polynomial fitting
• Kubelka–Munk model
• Spectral Neugebauer model
• Artificial neural network
Industrial applications:

- Sporting goods
- Automotive
- Toys and Gaming
- Houseware
- Entertainment
- Medicine
- Civic Engineering
- Architectural Models
- Art and Fashion
- Consumer electronic
• Colour 3D printing technologies

<table>
<thead>
<tr>
<th>Colour Technology</th>
<th>Company</th>
<th>Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td>PolyJet</td>
<td>Stratasys</td>
<td>UV-Cured</td>
</tr>
<tr>
<td>ColorJet Printing</td>
<td>3D Systems</td>
<td>Powder-binder</td>
</tr>
<tr>
<td>UV-curable inkjet</td>
<td>Mimaki</td>
<td>UV-Cured</td>
</tr>
<tr>
<td>MultiJet Fusion</td>
<td>Hewlett Packard</td>
<td>Powder-fusion</td>
</tr>
<tr>
<td>Laminated Object Manufacturing (LOM)</td>
<td>Mcor</td>
<td>Paper-binder</td>
</tr>
</tbody>
</table>

Colour control is much more complicated
Deep Neural Network

- Powerful
- Easy to implement
- Widely used for computer vision applications
Aim of this study

- Evaluate performance conventional colour characterisation models for colour 3D printers?
- Evaluate performance of Deep Neutral Network model for colour 3D printer
- Investigate factors affecting model performance
Colour Dataset

- Stratasys J750 3D printer
- 2016 data
- CMYK densities
- Spectral reflectance (400 nm - 700 nm)
- CIEXYZ and CIELAB
Input and Output Vectors

Input:
• CMYK values

Output:
• CIELAB
• CIE XYZ
• log(XYZ): the logarithm of CIE XYZ
• \( r \): spectral reflectance data
• PCA(\( r \)): principal components of Spectral data

The number of principal components of spectra data is defined as 6.

\[
\beta = (U_K)^T r \\
\]

\[
r = U_K \beta 
\]
• Least Square with $3^{\text{rd}}$ order Polynomial regression (PR)

\[ C = M \times P \]

\[ M = C \times P^{-1} \]

where $C$ represents the output vectors such as CIE XYZ or CIELAB, $P$ stands for the input CMYK values, $M$ is the colour characterisation model.
• Deep neural network (DNN)

Architecture of DNN:

- 4 fully connected layers
  The number of neurons in each FC layer: 21-77-21-3 / 22-66-33-31(6)

- 3 swisher layers

- The optimisation method: Adam

- The maximum epochs number: 2000

- The learning rate: 0.01

- 5 attempts
10-fold cross validation

- 90% of the total data set selected at random were used for training data (1814).
- The remaining 10% used for validation (202).
- Quantified using CIELAB colour-difference formula.
- The fitting procedure was performed 10 times.
- CIELAB colour differences under D65 illuminant.

<table>
<thead>
<tr>
<th></th>
<th>3rd PR</th>
<th>DNN</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Lab</td>
<td>XYZ</td>
</tr>
<tr>
<td>Mean</td>
<td>4.69</td>
<td>12.44</td>
</tr>
<tr>
<td>Median</td>
<td>3.95</td>
<td>10.26</td>
</tr>
<tr>
<td>Max</td>
<td>22.72</td>
<td>60.46</td>
</tr>
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</table>

Smaller colour differences
CIELAB colour differences under D65 illuminant.

<table>
<thead>
<tr>
<th></th>
<th>3rd PR</th>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Lab</td>
<td>XYZ</td>
<td>log(XYZ)</td>
<td>r</td>
<td>PCA(r)</td>
<td>Lab</td>
<td>XYZ</td>
<td>log(XYZ)</td>
<td>r</td>
<td>PCA(r)</td>
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<tr>
<td>Mean</td>
<td>4.69</td>
<td>12.44</td>
<td>5.74</td>
<td>11.74</td>
<td>12.05</td>
<td>1.59</td>
<td>2.69</td>
<td>1.49</td>
<td>2.34</td>
<td>1.84</td>
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<tr>
<td>Median</td>
<td>3.95</td>
<td>10.26</td>
<td>4.94</td>
<td>9.86</td>
<td>9.75</td>
<td>1.27</td>
<td>2.13</td>
<td>1.26</td>
<td>1.93</td>
<td>1.62</td>
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<tr>
<td>Max</td>
<td>22.72</td>
<td>60.46</td>
<td>20.63</td>
<td>45.16</td>
<td>46.34</td>
<td>9.25</td>
<td>18.53</td>
<td>5.52</td>
<td>11.19</td>
<td>7.82</td>
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</table>

Larger colour differences
Model Performance

- Histograms of CIELAB colour differences under D65 illuminant.

- The method of DNN achieved smaller colour differences than the 3\textsuperscript{rd} PR.
Effect of Different Training Data Sizes

- Randomly selecting 5% - 95% of the dataset as the training data
- The remaining as the testing data
- Perform 10 times

The number of training and testing data:

<table>
<thead>
<tr>
<th>Number</th>
<th>5%</th>
<th>10%</th>
<th>15%</th>
<th>20%</th>
<th>25%</th>
<th>30%</th>
<th>35%</th>
<th>40%</th>
<th>45%</th>
<th>50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>101</td>
<td>202</td>
<td>302</td>
<td>403</td>
<td>504</td>
<td>605</td>
<td>706</td>
<td>806</td>
<td>907</td>
<td>1008</td>
</tr>
<tr>
<td>Testing</td>
<td>1915</td>
<td>1814</td>
<td>1714</td>
<td>1613</td>
<td>1512</td>
<td>1411</td>
<td>1310</td>
<td>1210</td>
<td>1109</td>
<td>1008</td>
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<tr>
<td>55%</td>
<td>1109</td>
<td>1210</td>
<td>1310</td>
<td>1411</td>
<td>1512</td>
<td>1613</td>
<td>1714</td>
<td>1814</td>
<td>1915</td>
<td></td>
</tr>
<tr>
<td>60%</td>
<td>907</td>
<td>806</td>
<td>706</td>
<td>605</td>
<td>504</td>
<td>403</td>
<td>302</td>
<td>202</td>
<td>101</td>
<td></td>
</tr>
</tbody>
</table>
Model Evaluation

- The CIELAB colour differences using different training data sizes

**3rd polynomial regression**

- Keep stable

**Deep neural networks**

- Decreasing
### Processing time

Time spent in **each fitting process**

<table>
<thead>
<tr>
<th>Laptop</th>
<th>3rd PR</th>
<th>DNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training (1814)</td>
<td>≈ 0.02 seconds</td>
<td>≈ 15 minutes</td>
</tr>
<tr>
<td>Testing (202)</td>
<td>≈ 0.01 seconds</td>
<td>≈ 0.5 seconds</td>
</tr>
</tbody>
</table>

- Laptop: Intel® Core™ i5-1035G1 CPU processor
- Matlab
### Model Performance

- Spectral estimation
- Quantified using the $\text{RMSE}$ (root-mean-square error)

<table>
<thead>
<tr>
<th></th>
<th>PR + $r$</th>
<th>PR + PCA($r$)</th>
<th>DNN + $r$</th>
<th>DNN + PCA($r$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{RMSE}$</td>
<td>0.0206</td>
<td>0.0218</td>
<td>0.0051</td>
<td>0.0048</td>
</tr>
</tbody>
</table>
9 examples:

- Blue curves: the predicted spectral data
- Orange curves: the measured spectral reflectance

3rd polynomial regression

Deep neural networks
Model Evaluation

- The RMSE using different training data sizes
**Summary**

- The method of DNN has better performance than the 3\textsuperscript{rd} PR.
- Better spectral estimation was achieved using the DNN method.
- CIE XYZ as the output of colour characterisation produced larger colour differences.
- CIELAB and the logarithm of CIE XYZ are recommended as the output of colour characterisation.
- As the training data size increases, the 3\textsuperscript{rd} PR method yielded stable results, while an optimal number of training data is required for the DNN method.
Future work

- Investigate how training colour sample selection to performance DNN
- Improve efficiency of DNN (performance vs. number of coefficients)
- Verify whole colour management pipeline (for example display to printer)
- Apply colour transform to colour images
Thanks for your attention

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