



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



Printer Colour Characterisation



Forward colour characterisation

Reverse colour characterisation

CMYK to CIELAB:



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



3D Full Colour Printing



Industrial applications:

- Sporting goods
- Automotive
- Toys and Gaming
- Houseware
- Entertainment

- Medicine
- Civic Engineering
- Architectural Models
- Art and Fashion
- Consumer electronic



3D Full Colour Printing



Colour 3D printing technologies

Colour Technology	Company	Technology		
PolyJet	Stratasys	UV-Cured		
ColorJet Printing	3D Systems	Powder-binder		
UV-curable inkjet	Mimaki	UV-Cured		
MultiJet Fusion	Hewlett Packard	Powder-fusion		
Laminated Object Manufacturing (LOM)	Mcor	Paper-binder		

Colour control is much more complicated

Deep Neutral Network



• Powerful

• Easy to implement

 Widely used for computer vision applications





- 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.

$$\beta = (U_K)^T r$$
$$r = U_K \beta$$



Mathematical approach I



• Least Square with 3rd 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.

Mathematical approach II



• 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



Model Evaluation



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.

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

Smaller colour differences



• CIELAB colour differences under D65 illuminant.

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

Larger colour differences



• Histograms of CIELAB colour differences under D65 illuminant.



• The method of DNN achieved smaller colour differences than the 3rd PR.

Effect of Different Training Data Sizes UNIVERSITY OF LEEDS

- 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:

Number	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%
Training	101	202	302	403	504	605	706	806	907	1008
Testing	1915	1814	1714	1613	1512	1411	1310	1210	1109	1008
	55%	60%	65%	70%	75%	80%	85%	90%	95%	
Training	1109	1210	1310	1411	1512	1613	1714	1814	1915	
Testing	907	806	706	605	504	403	302	202	101	

Model Evaluation

3rd polynomial regression



• The CIELAB colour differences using different training data sizes



Deep neural networks

Keep stable

Decreasing

Processing time



Time spent in each fitting process

Laptop	3 rd PR	DNN
Training (1814)	≈ 0.02 seconds	\approx 15 minutes
Testing (202)	≈ 0.01 seconds	≈ 0.5 seconds

- Laptop: Intel® Core™ i5-1035G1 CPU processor
- > Matlab



- Spectral estimation
- Quantified using the *RMSE* (root-mean-square error)

	PR + <i>r</i>	PR + PCA(<i>r</i>)	DNN + r	DNN + PCA(r)
RMSE	0.0206	0.0218	0.0051	0.0048



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



Model Evaluation



• The RMSE using different training data sizes



Summary



- The method of DNN has better performance than the 3rd 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 3rd 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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