

Hyperspectral Image Segmentation for Paint Analysis

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1. Introduction

Hyperspectral imaging techniques are used in the field of restoration of artworks As a means of non-destructive analysis. Most research regarding hyperspectral imaging focus on the classification of these pigments. In [1] a superpixel segmentation algorithm was applied on hyperspectral data to segment regions in a homogeneous manner. This, however, results in over-fragmentation of visually large segments. In this work, we aim to improve this over-segmentation by introducing Spectral Similarity Merging (SSM), a region merging approach that is based on spectral similarity. This should ease the restorers interpretation of the data and provides them with guidelines for pigmentation without oversegmenting the regions.

2. Methods

Data is acquired using a SPECIM FX10e camera which provides 448 spectral bands in the range of 400-1000nm with an average resolution of 1.33nm. Winsor & Newton pigments were used to create the following types of samples of: individual paint regions and mixed paint regions. Figure 1 illustrates the proposed segmentation process in its entirety, starting with data acquisition, the proposed segmentation process and visualisation of results.



Figure 1 – A block diagram describing the process.



3. Results

The proposed segmentation process consists of three main stages; Region Merging, Pixel Re-assignment, and Further Merging, as shown in Figure 1. Each stage contributes toward less over-segmentation by effectively merging regions that have similar spectral signatures. The results for each stage are illustrated in Figure 2.

As observed, the results show a considerable reduction in over-segmentation when compared to the Simple Linear Iterative Clustering (SLIC). Moreover, the algorithm adheres to boundaries very well in comparison to SLIC. When

Table 1 – Comparison of metrics for SLIC and SSM. Over-Segmentation (OS) and Under-Segmentation (US) are optimal at 0, while Recall (R), Precision (P) and F1-Score (F1) are optimal at 1.

	Method	US	OS	R	Р	F1
lmage1	SLIC	0	0.95	1	0.05	0.10
	SSM	0.07	0.41	0.92	0.59	0.72
Image 2	SLIC	0.01	0.94	0.99	0.06	0.12
	SSM	0.14	0.54	0.84	0.45	0.59
Image 3	SLIC	0	0.95	1	0.05	0.09
	SSM	0.06	0.50	0.93	0.50	0.64
Image 4	SLIC	0.01	0.91	0.98	0.09	0.16
	SSM	0.11	0.50	0.84	0.50	0.62

comparing for other mock-up images in Table 1, one can observe how these improvements are consistent, and more importantly, over-segmentation (OS) reduction is achieved without a huge loss in under-segmentation (US). In terms of precision (P) and recall (R), a huge improvement on precision can be observed. This occurs because the amount of false positives is decreased, while the amount of false negatives remains fairly the similar, which causes the F1-Score (F1) to increase when compared to SLIC.

The proposed method has also been tested on a mock-up sample image in which two very similar red paints are found to be adjacent to each other. The algorithm manages to separate these regions, whereas for SLIC, it is not quite visually clear that the region boundary for the reds is captured, as shown in Figure 3.

4. Conclusion

We proposed Spectral Similarity Merging (SSM), a region merging algorithm based on spectral similarity. Results show that the proposed algorithm performs



very well when compared to other state-of-the-art algorithms such as SLIC. In fact, F1- Score measures improve by an average of 52%, whereas oversegmentation is improved by an average of 45%. More importantly, the algorithm is capable of separating similar hue paints such as reds, while keeping over-segmentation at low amounts.

Figure 3 – An image containing two similar adjacent red paints (a) Result for SLIC (b) Result for SSM (C).

References

[1] Radhakrishna Achanta et al (2012). SLIC Superpixels Compared to State-of-the-Art Superpixel Methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 34, No. 11, 2012.*