Can we date an artist's work from catalogue photographs?

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***Abstract*—Kyffin Williams, art changes over time, blah blah blah. Features, colour, edges, histograms of oriented gradients; strong correlation using leave-one-out methodology. Exemplars; artistic and statistic.**

I. Introduction

This paper presents a interdisciplinary computational study into the modelling of artistic style, and how this style changes over time. The artist Sir John (Kyffin) Williams painted from X to 2004, and produced a good many paintings during this period – he was a prolific painter. His style evolved from a very figurative, representational style, to something more abstract: the computer scientists on our team would say that the paintings became more *blocky*; the art historians that *XXXwhatever lorna and lloyd want to say*. Through a collection of digital photographs of oil paintings, collected from museum websites, catalogues and other sources, we first investigate whether it is possible to date a painting from an unknown year based upon image features alone.

XXX mention key features of Kyffin's work, Patagonia, where he painted

II. Background

A. A digital humanities approach to art history

B. Computer vision and the analysis of paintings

XXX in here we will need refs to that work on van gogh, to the guy who wrote the review paper, and to anything else on computer analysis of paintings that is relevant. What we're looking for are 5+ references, going from the general (massive review paper) to the specific (image processing to analyse artistic style). Bonus points for freshness - we don't really want to cite anything older than 10 years. Can you copy and paste some stuff from your MPR? Doesn't matter if it's too long I'll hack it back.

III. The image dataset

Our image dataset consists of 325 paintings, with associated metadata. Metadata includes title, year or year ranges (for those works where year is unknown but can be estimated by curators), genre, original painting size, painting materials and image size.

These photographs of paintings are challenging in and of themselves: they are not colour calibrated; some suffer from reflections (towards the end of his life Kyffin painted using exceptionally thick and textural strokes, which gives specularities on the catalogue images); they are at varying resolutions; and come from a range of different cameras. Image size bears little relation to the original painting size, and some images are even optimised for the web. Table I below summarises the dataset

Type	Number	Number (Known date)	Notes
Landscapes	247	64	
Portraits	52	35	
Seascapes	11	2	
Still lifes	4	1	
Other	8	0	Genre unknown or studies

TABLE I. A summary of the Kyffin Williams painting dataset used

XXXIt may be worth putting in something here about image size vs painting size?

IV. Methodology

Within our database of 325 paintings, we know the actual year of painting for 102 artworks. In order to determine the accuracy of our results, rather than work with the full dataset (and work with images with uncertain metadata in the form of date ranges), we have used a leave-one-out cross validation methodology. This involves us taking a painting for which we know the year, and then using our classifier to guess that year; thus we are able to tell whether we are right. We are also able, if we are wrong, to determine exactly how wrong we are.

To simplify the classification stage we use a K-Nearest Neighbour (KNN) classifier with the other 101 paintings for which we know the date. KNN is a fast, non-parametric classifier which makes no assumptions about the underlying patterns in the data, merely that paintings from around the same time will be similarly located in our feature space(s). Whilst we suspect that there may be some broader underlying trend in the change of style, for this work have concentrated on features

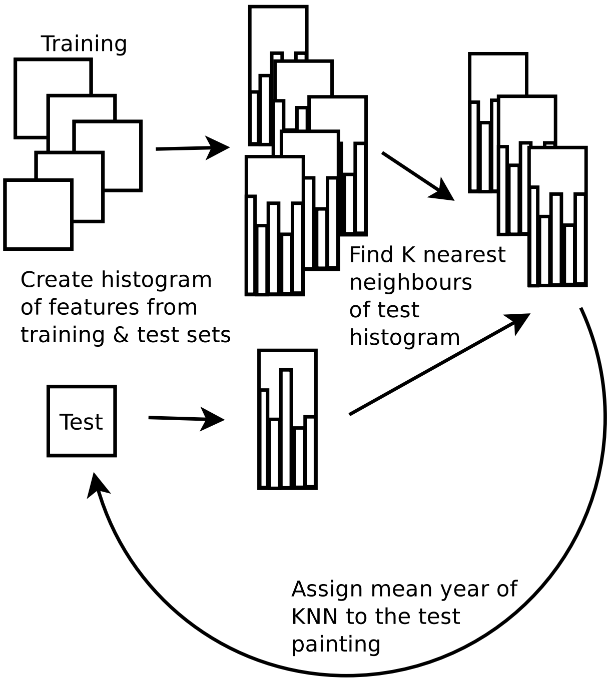

Fig. 1. Overview of the classification methodology

for classification rather than the question of classification or regression itself.

Thus for each feature set, we take all paintings for which we know the year of creation; select one painting, and find its nearest neighbours within that feature space. The year assigned by our classifier to that painting is the XXXMEAN/MED/MODE? Figure 1 provides an overview of this classification methodology.

We also know that painting's actual year, and we can plot actual against predicted year for all known-year paintings. To measure goodness of fit, the Pearson's product-moment correlation coefficient was calculated on these orderings; this provides us with a performance measure of each classifier. It is also possible to test Pearson's R for statistical significance; thus significance levels are reported alongside R in this paper.

XXX Thought: You can test Pearson's for statistical significance - can we try this? http://www.vassarstats.net/textbook/ch4apx.html Should not require much change to your code.

V. AN EXPLORATION OF COLOUR AND TEXTURE FEATURES

The digital analysis of paintings is a broad reseach area. Within the methodology we have selected, there are many feature spaces which could be useful: from simple analysis of the way in which colour changes over time, through edge detection, to texture analysis and maybe even brush-stroke recognition. Within this work we have concentrated on lower level image features – colours, textures, and edges – rather than attempt to extract brush strokes. Kyffin Williams painted with a pallette knife rather than a brush, and his work is characterised by angularity rather than identifiable "strokes".

As there is a clear (to the eye) trend in colour usage, as the paintings get "gloomier" over time, we started with simple colour-space analysis: taking the mean RGB for each painting and using this with our KNN classfier; we also tested other colour spaces, such as HSV. Promisingly this provided us with a positive correlation. With all of these analysis techniques we treat the results as histograms, this allows us to use a single distance measure, namely chi-squared, for k-nearest neighbour.

Staying with the colour variation theme, we then used colour histograms, which provide a more precise representation of the way Kyffin Williams used colour. These histograms were developed by counting the number of pixels within a particular colour range for each painting, and then building a normalised histogram representing the colour usage.

As a lot of Kyffin Williams' paintings are highly textural, edge detection and texture analysis were thought to be good techniques to explore.

Edge detection involved applying one of the various edge detection algorithms available, applying it to each painting. The distance measure is base on the number and strength of edges in the painting. Canny[1] edge detection is a reasonable algorithm for this.

Texture analysis is a continuation of edge detection. Instead of just taking the strength and number of edges, we create a histogram of orientated gradients as in [2]. In this way we begin to build up a richer representation of the texture of a painting. Given the change in style of Kyffin Williams' work, moving away from figurative representations with curved lines towards more blocky rectilinear brush strokes, we expect these edge orientation frequencies to change over time. To this end we used simple steerable filters S, applied to the image at 0, $\frac{\pi}{4}$, $\frac{\pi}{2}$ and $\frac{3\pi}{4}$.

$$S\left(\frac{\pi}{2}\right) = \begin{pmatrix} 0 & 0 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix} \quad (1)$$

Equation 1 shows a sample steerable filter, in this case $S(\frac{\pi}{2})$, the filter which gives the highest response when presented with horizontal lines. By convolving each image with filters tuned to different orientations, we can build a histogram recording the frequency of lines at each orientation.

XXX Can we have a visualisation of this? perhaps a picture with its associated histogram? maybe a crop from this blog http://users.aber.ac.uk/adb9/?e=27 but maybe we want to make the visualisation a bit more stand out...

Gabor filters were also used with a greater range of angles to produce a more accurate representation of the texture of the painting.

$$g_e(x) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x}+\frac{y^2}{\sigma_y}\right)} \cos(2\pi\omega_{x_0}x + 2\pi\omega_{y_0}y) \quad (2)$$

Where $(\omega_{x_0}, \omega_{y_0})$ defines the centre frequency, and (σ_x, σ_y) the spread of the Gaussian window.

XXX Again, can we get a visualisation? What does Gabor give us that steerable filters don't (apart from scary mathematics?)

Another method for producing histograms of orientated gradients is to apply two discrete derivative masks to the image to get the gradient of x and y and then to work out the gradient direction at each point. This can then have a histogram created from it to provide a different representation of the texture of the image.

XXX Right oh now what we need is some graphs I suggest for now doing results in-line, or have a table here showing correlation coefficients

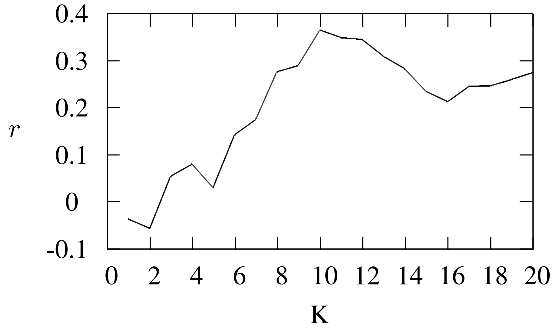

Fig. 2. Correlation Coefficients r against K values for K-Nearest Neighbour on Histogram Analysis

XXX you're not going to like me for this but can you plot the other feature spaces too?

The one parameter of our classifier is the choice of K in K-nearest neigbour. Simply setting $K = 1$ has the effect of assigning the year of the nearest painting in feature space to the current test painting, whereas setting $K = 102$ has the effect of giving each painting the mean value of the entire dataset. Clearly a point between these two extremes would be best; from Figure 2 we can see that for many of the feature spaces we consider, the optimum K value is around 10.

Technique	r	$P(r)$
RGB		
HSV		
HSV Histogram	0.364	0.00007
Edge Strength		
HOG		

TABLE II. CORRELATION COEFFICIENTS

VI. EXEMPLARS: CAN WE IMPROVE RESULTS BY INCORPORATING EXPERT KNOWLEDGE?

For exemplar-based classifiers the result of the classification was a new point in space, the statistically-chosen exemplar, which was then compared to an existing point in space, the artistically-chosen exemplar. The performance measure applied to each classifier was the squared error of the distance from the statistically-chosen exemplar to the artistically-chosen exemplar.

The data on artistically-chosen exemplars opened up the options for different methods of classification. Rather than using a k-nearest neighbour algorithm to classify each point in the feature space we could just take the year of the nearest exemplar to that point and use that for classification.

This then raised the question as to what the digitally-chosen exemplars would be. Statistically exemplars would be the centroid of a group of paintings in feature space; a relatively simple operation to perform digitally.

A. *Comparing Artistic and Statistical Exemplars*

The same distance measure used to run k-nearest neighbour on the feature-based classifiers was used to generate the error between the statistical and artistic exemplars.

VII. CONCLUSION

ACKNOWLEDGMENT

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REFERENCES

[1] J. F. Canny, "A computational approach to edge detection," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. PAMI-8, no. 6, pp. 679–698, Nov. 1986. [Online]. Available: http://dx.doi.org/10.1109/tpami.1986.4767851

[2] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, ser. CVPR '05, vol. 1. Washington, DC, USA: IEEE, Jun. 2005, pp. 886–893 vol. 1. [Online]. Available: http://dx.doi.org/10.1109/cvpr.2005.177