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

[1] defines a method of analysing brush-strokes by moving a circular filter across the whole painting to find the ridges of strokes, then filling any unbroken areas. They then shrunk these areas to a single pixel line and fitted a n^{th} order polynomial to this line. This method seems fairly simplistic, but could be an interesting first step, but as it is more focused on authenticating paintings it may be of limited use.

Another method for stroke analysis has been published in the IEEE Transactions on Pattern Analysis and Machine Learning journal. This method is far more complex, but is able to extract and label individual brush-strokes. An interesting part of their findings was the ability to date some of Van Gogh's paintings to a known period in his career[2].

This method involves performing edge detection of the painting followed by an edge linking algorithm which aims to remove small, noisy edges and to trace every edge. With this they then perform enclosing, as strokes may not be complete this stage also aims to fill in missing gaps of strokes and to fill these in within a certain tolerance.

The algorithm then decides if a stroke really is a painted stroke, if the stroke is completely enclosed, isolated from other non-edge pixels and forms a connected component then it is likely that it is a proper brush-stroke and is extracted. The edge pixels are used as the background and the non-edge pixels as the foreground, this is the process of labelling the brush-stroke.

For each of these labelled candidates, a heuristic function is used to threshold any brush-strokes that are either too long or too short, these strokes are discarded. These strokes are then considered to be candidates if they are not significantly branched, the stroke is not too wide (this may change for Kyffin Williams as he used a pallet knife rather than a brush) and the brush-stroke is not too big or small.

Separately, the image is then segmented using k-means clustering by RGB values. This clustering algorithm is applied several times, lowering the tolerances for distance within a cluster. Connected components as a result of this clustering and have noise reduction performed upon them. Finally, the two types of brush-strokes are combined.

This technique may need some changing to account for Kyffin Williams' use of a pallet knife, but the overall principals of this technique should work with Kyffin's paintings.

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 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 mean of the K neighbours. 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.

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

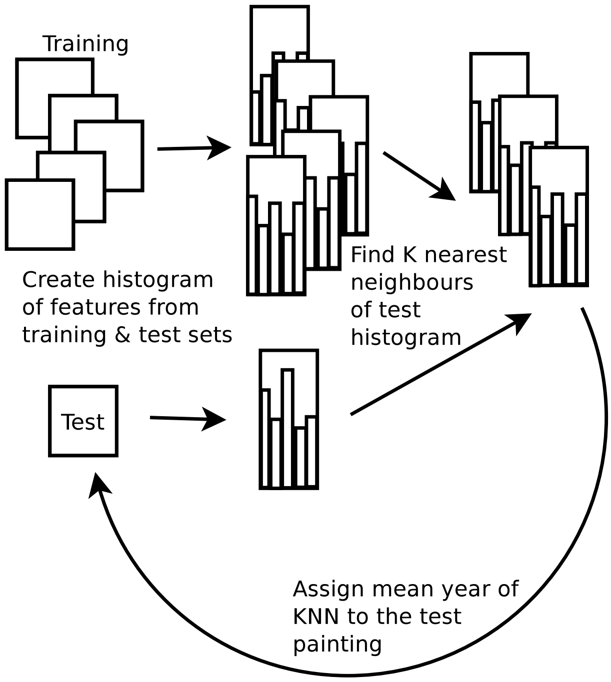

Fig. 1. Overview of the classification methodology

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[3] 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 [4]. 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 $\frac{3\pi}{4}$.

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

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.

Fig. 2. Example image

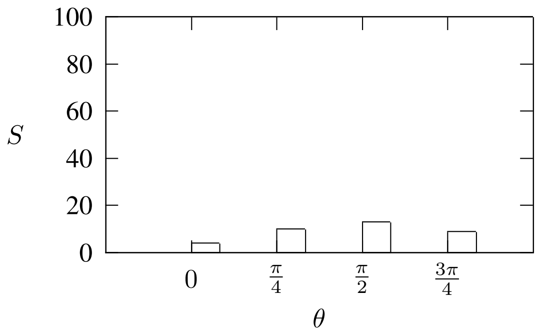

Fig. 3. Steerable filter strength $S(\theta)$ on the example image in figure 2

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.

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

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.

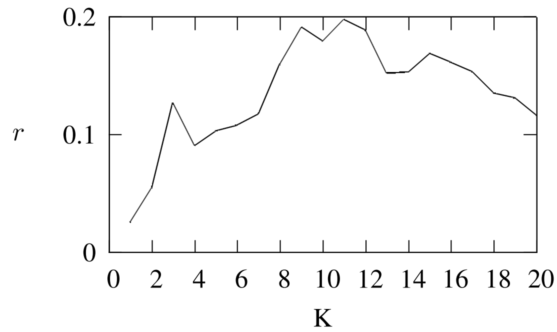

Fig. 4. Correlation Coefficients r against K values for K-Nearest Neighbour on RGB Colour-Space Analysis

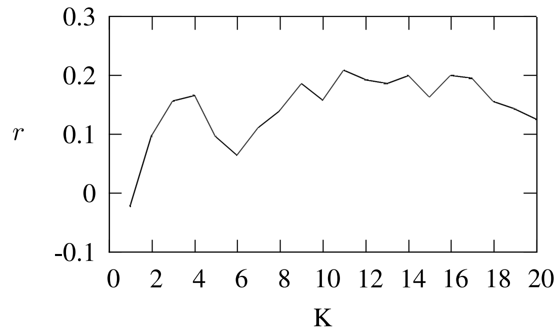

Fig. 5. Correlation Coefficients r against K values for K-Nearest Neighbour on HSV Colour-Space Analysis

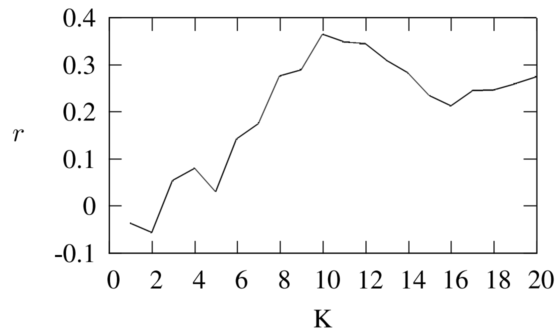

Fig. 6. Correlation Coefficients r against K values for K-Nearest Neighbour on Histogram Analysis

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

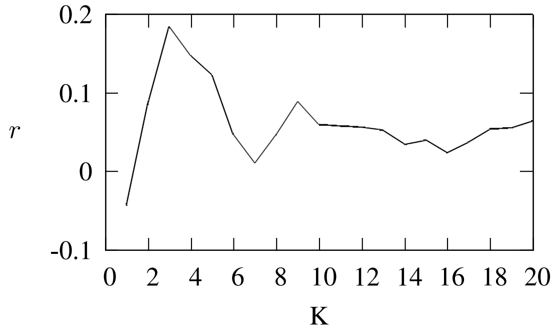

Fig. 7. Correlation Coefficients r against K values for K-Nearest Neighbour on Edge Strength Analysis

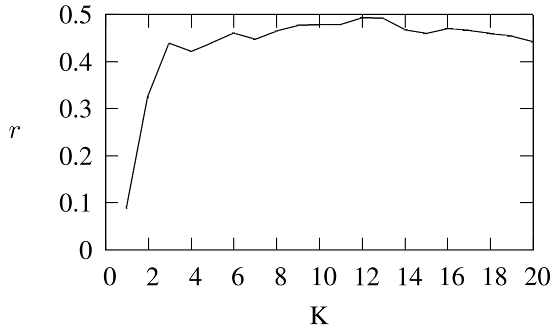

Fig. 8. Correlation Coefficients r against K values for K-Nearest Neighbour on HOG Analysis

effect of giving each painting the mean value of the entire dataset. Clearly a point between these two extremes would be best; from Figure **??** we can see that for many of the feature spaces we consider, the optimum K value is around 10.

Technique	r	$P(r)$
RGB	0.179	0.05757
HSV	0.158	0.09518
HSV Histogram	0.364	0.00007
Edge Strength	0.060	0.52877
HOG	0.479	0.00000008

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

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