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

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***Abstract*—Computer vision has addressed many problems in art, but has not yet looked in detail at the way artistic style can develop and evolve over the course of an artist's career. In this paper we take a computational approach to modelling stylistic change in the body of work amassed by Sir John "Kyffin" Williams, a nationally renowned and prolific Welsh artist. Using images gathered from catalogues and online sources, we use a leave-one-out methodology to classify paintings by year; despite the variation in image source, size, and quality we are able to obtain significant correlations between predicted year and actual year, and we are able to guess the age of the painting within 15 years, for around 70% of our dataset. We also investigate the incorporation of expert knowledge within this framework by consdering a subset of paintings chosen as *exemplars* by a scholar familiar with Williams' work.**

I. Introduction

This paper presents a interdisciplinary computational study into the modelling of artistic style, and how this style changes over time. Sir John Kyffin Williams (1918-2006) was one of the predominant figures in Welsh art of the twentieth century. Kyffin – as he was almost universally known in Wales – studied at the Slade School of Art and worked as an art master at Highgate School, before returning to live on his native Anglesey in 1973. He was a prolific painter and once claimed to have painted "two pictures per week when in London, and three per week when in Wales.'[1, p.209] With a career spanning from the mid-1940s to approximately 2004, this rate amounts to a large body of work.

His technique evolved from a very representational style to something more expressive, which retained representational qualities: the computer scientists on our team would say that the paintings became more *blocky*; the art historians that his landscapes are almost constructed with swathes of textural paint. His was a style characterised by thick impasto paint, applied almost exclusively with palette knife, although the application technique appears to change over time. This development of style led us to wonder: is it possible to date the pictures from images alone?

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 based upon image features. We show that using a K-nearest neighbour classifier, tested using a leave-one-out methodology, we can obtain a strong correlation between image feature descriptors and year of painting. We go on to investigate whether exemplar based methods are able to improve on this, using what we call *artistic exemplars* (paintings selected by an expert as being typical for a particular year) and *statistic exemplars* (paintings which are near the centre of year-based clusters in feature space).

II. Background

Although also a portrait painter, Williams is primarily known for his landscape paintings of north west Wales and Anglesey. While his technique and style changed over the years, his landscapes in oil are instantly recognisable, often featuring bold chunks of colour, and various points during his career bold black outlines to figures and landscapes features. Greens, browns and greys often form the palette of his paintings of the Welsh landscape. These colour selections seem appropriate for the artists claim that melancholy, derived from the "dark hills, heavy clouds and enveloping sea mists", is a national characteristic of the Welsh [1]. This combination of colour selection and technique seems appropriate for the depiction of the areas where he painted. Many of his most successful paintings are said to have a "dark quality" in depicting "rain lashed hillsides," and it was this darkness which "makes his landscapes so distinctively Welsh" [2]. Figure 1 shows an early Williams painting, complete with rain lashed hillsides.

The aesthetic of Williams's Welsh landscapes is contrasted by the paintings he made following a trip to Patagonia to paint the landscape and people of the Welsh communities there in 1968 as part of a Winston Churchill Foundation scholarship. The colours and application of paint in pictures produced in following this journey (such as *Lle Cul*, *Henry Roberts*, *Bryngwyn Patagonia*, *Euros Hughes Irrigating his Fields*, all 1969, National Library of Wales) differ starkly from paintings of Welsh landscapes, incorporating pinks, purples and oranges. This contrast, combined with the fact that the Patagonian pictures were produced during a definite period of time has reinforced our interest in the analysis of the formal qualities of pictures from different collections remotely, using digital images.

Fig. 1. "*Snowdon, the Traeth and the Frightened Horse*", Sir John Kyffin Williams, 1948: note curved strokes, rather than blocky application

Williams's work is well represented in public collections in Wales (particularly at the National Library of Wales, the National Museums and Galleries of Wales and Oriel Ynys Môn, Anglesey). His pictures, often depicting the landscape and people of north-west Wales were also tremendously popular with the art buying public. Of the 325 paintings by Williams in public collections in the UK listed on the BBC/Public Catalogue Foundation's "Your Paintings" website, 212 of them are in the collections of the National Library of Wales [3]. Many of these paintings were bequeathed to the Library as part of a larger bequest by the artist (including works on paper and other archival material). Many of the pictures which came to the library from the artists studio had little in the way of metadata, and as such have been catalogued with large date-ranges estimating the dates of production. This uncertainty in metadata is another motivating force behind the current project.

A. *Taking a digital humanities approach to art history*

Digital humanities is an established area of research that brings together digital content, tools and methods in order to address and create new knowledge across the disciplines. Digital humanities approaches can be seen in two distinct types of inquiry. The first is to carry out *traditional* humanities research more effectively or efficiently, by applying computational methods or approaches to digitized humanities sources (originally text, image, or audio-visual content from archives or libraries). Using John Unsworths definition of "scholarly primitives" [4] digital humanities scholarship customarily involves the use of digital tools and methods for discovering, annotating, comparing, referring, sampling, illustrating, or representing humanities data. A classic example of this sort of work would be the use of concordances and other computer-based analysis of digitized primary sources that have been processed by optical character recognition software to count, classify, or interpret digital texts (see, for example, the Historical Concordance of the Welsh language [5]). The second strand of digital humanities inquiry is the development of new research questions that can only be developed through the synthesis of digital content, tools and methods: work that would have otherwise been unimaginable [6]. This type of research is by necessity multi-disciplinary, drawing together expertise to be found across humanities, scientific and engineering disciplines, as well as involving content experts from libraries, archives and museums. However, in order to be truly transformative, this type of research must also be interdisciplinary.

The National Library of Wales now has a research programme in digital collections, which is a forum for investigation into the digital collections of Wales in collaboration with academics and students at universities in Wales and beyond, in order to develop new research based around the digital content created by the Library [7]. The research project described in this article is an example of a digital humanities collaborative venture, bringing together digital humanists, art historians, and computer scientists. The results of this research have value across all these groups. Arts historians are able to better investigate a large corpus of digital paintings through the application of computer science approaches to this content, and computer scientists are able to configure new approaches in imaging to working with a complex humanities data set.

B. *Computer vision and the analysis of paintings*

Stork, in his 2009 review paper, presents an overview of the field of digital painting analysis [8]. Leaving aside structural aspects of painting analysis (for example, there is a rich seam of work looking at the geometry of figurative art, for example [**?**]) most work in the area of style analysis is aimed at authentication. With the problem of authentication, one tries to build a two class classifier for a painter where the classes in question are "painted by artist X" or "not painted by X" (e.g. Irfan and Stork's feature based classifier for authenticating Jackson Pollock artworks, [**?**]).

When we consider computer vision-based analysis of painterly style we find that the vast majority of work concentrates on brush stroke detection and analysis. For example, Berezhnoy and colleagues in [9] detect 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.

Li et al [10] use a combination of edge analysis and clustering in colour space to determine strokes; a number of heuristics involving branching, stroke-width modeling, and gap filling are then used to refine the original brush stroke estimates. One interesting element of this work, from our perspective, is the ability to date some of Van Gogh's paintings to a known period in his career. To the best of our knowledge this is the only other work which aims, like us, to date work: that is, to automatically place an artwork in the context of the artists' own body of work.

Techniques based upon stroke analysis, whilst applicable to the work of some artists, are not applicable to all. In particular, Kyffin Williams painted with a palette knife and whilst there are clear *strokes* identifiable in his style, these vary widely in size and shape, so the morphological techniques which can detect strokes in Van Gogh's work are unlikely to pay off when considering the blockier paintings in the Williams oeuvre. Another difference of note is that much work on computerised painting analysis (including [10], [9]) is based upon high resolution scans acquired in controlled conditions, whereas the current paper deals instead with a collection of photographs from catalogues, websites, and other disparate sources.

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; Figure 2 shows a late Williams painting.

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

TABLE I. A SUMMARY OF OUR KYFFIN WILLIAMS PAINTING DATASET

Fig. 2. "*Above Carneddi, No. 2*", Sir John Kyffin Williams 1985: note much blockier style and changed use of colour

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; we found this provided better results than both median and mode. Figure 3 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. With all of the feature spaces we consider, it is possible treat the painting descriptors as histograms. This allows us to use a single distance measure, namely chi-squared, in our K-nearest neighbour classification.

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

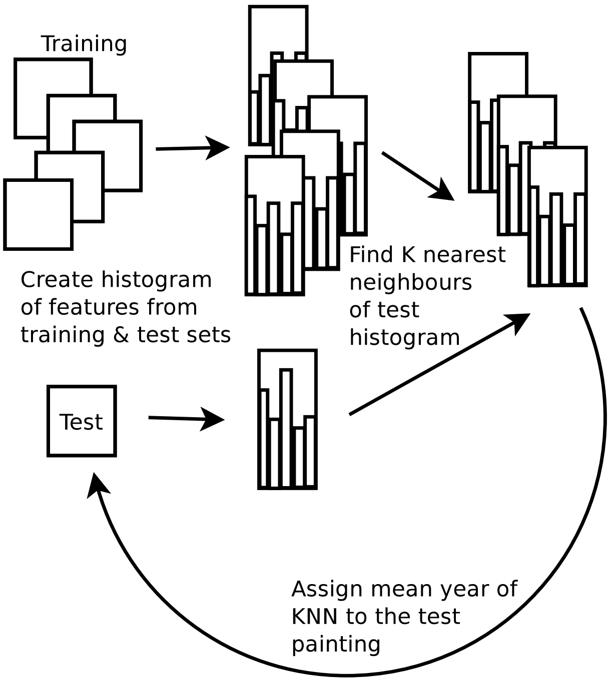

Fig. 3. Overview of the classification methodology

of the way in which colour changes over time, through edge detection, to texture analysis. We have concentrated on lower level image features – colours, textures, and edges – rather than attempt to extract brush strokes. As mentioned earlier, Williams painted with a pallette knife rather than a brush, and his work is characterised by angularity rather than identifiable "strokes". Our motivation for this is not only due to these issues with painterly style, but also because of the variation in image quality. By concentrating on simpler features we hope to retain some robustness to variation in image capture and quality. In this section we describe the various feature sets and feature spaces we have explored; results for each of these are presented in Section VI below.

There is a clear (to the eye) trend in colour usage, as the paintings get "gloomier" over time. Thus, 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. Remaining with the colour variation theme, we then used colour histograms, which provide a more precise representation of the way 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 also thought to be a good avenue to explore. Firstly, we investigated simple *edginess*; as a rough estimate of the the edge properties of the artworks we apply a Canny [11] edge detector to the paintings, and then use a count of edge pixels as our feature.

Texture analysis can be thought of as a continuation of edge detection. Instead of taking simply the strength and number of edges, we create a histogram of orientated gradients as in [12]. 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. Figures 4 and 5 show a painting, and the resulting edge orientation histogram; it is clear from this that there are more horizontal edges in this particular image due to the clear peak at $\frac{\pi}{2}$.

Fig. 4. "*Coastal Sunset*", Sir John Kyffin Williams. Date unknown, thought to be in the range 1990-2006

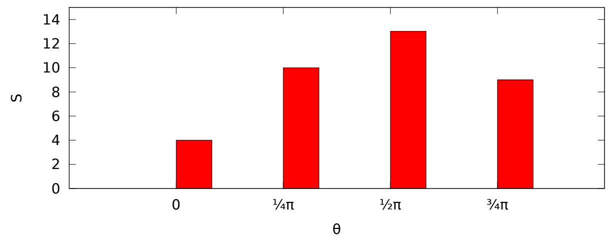

Fig. 5. Steerable filter strength $S(\theta)$ on the example image in figure 4

Gabor filters are linear filters which can be tuned to a greater range of angles and frequencies than simple steerable filters, which in turn results in a more accurate representation of the texture of the painting. The general equation for a Gabor filter is given in Equation 2.

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

Where $(\omega_{x_0}, \omega_{y_0})$ defines the centre frequency, and (σ_x, σ_y) the spread of the Gaussian window [**?**]. In this work we use Gabor filters tuned to equally spaced orientations to build a histogram representing line orientations in each painting, and present results below for histograms built from the output of 4, 8 and 16 filter orientations.

The final method for producing histograms we consider involves the application of 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. These gradient directions are then summarised in a histogram of oriented gradients, providing a yet richer representation of the texture of the image. This is similar to the method described in [12]; again we present results on the output of 4, 8 and 16 orientations.

VI. YEAR CLASSIFICATION RESULTS

The one parameter of our classifier is the choice of K in K-nearest neighbour. 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 6 we can see that for many of the feature spaces we consider, the optimum K value is around 7 or 8. Pearson's correlation coefficients r for K=7, alongside $P(r)$ are presented in Table II. A further measure of classification accuracy is also presented: this is the percentage of paintings for which our classifier manages to date the artwork in question within 15 years of actual painting date. This measure, $C(n)$, provides an easy to understand measure of classification accuracy.

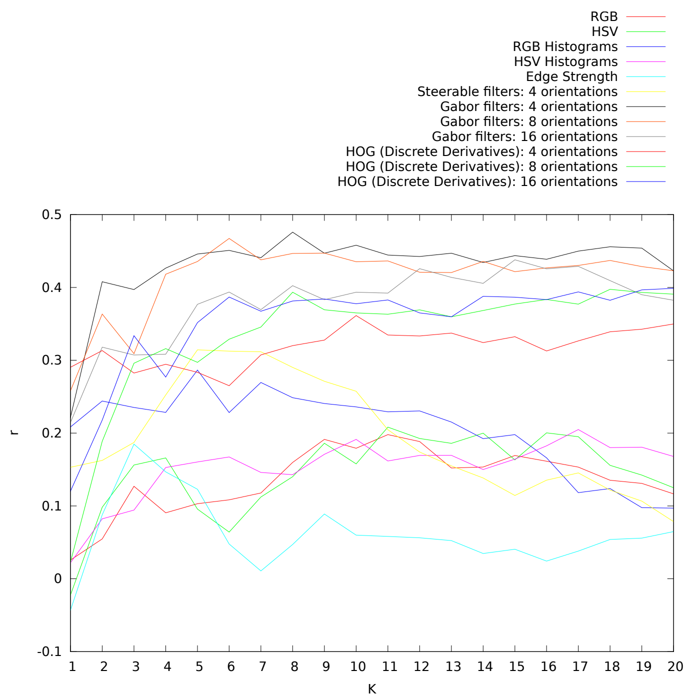

Fig. 6. Correlation Coefficients r against K values for K-Nearest Neighbour

From Table VI it is clear to see that whilst the dates predicted by our methods correlated fairly well with the actual painting dates, and these correlations are mostly significant,

Technique	r	$P(r)$	$C(15)$
Edge Strength	0.0107	0.910	60%
HSV	0.112	0.237	64%
RGB	0.118	0.214	63%
HSV Histograms	0.146	0.123	64%
RGB Histograms	0.270	0.004	62%
HOG (Discrete Derivatives): 4 orientations	0.307	0.001	65%
Steerable filters: 4 orientations	0.312	0.001	68%
HOG (Discrete Derivatives): 8 orientations	0.346	<0.001	65%
HOG (Discrete Derivatives): 16 orientations	0.367	<0.001	64%
Gabor filters: 16 orientations	0.370	<0.001	67%
Gabor filters: 8 orientations	0.438	<0.001	70%
Gabor filters: 4 orientations	0.441	<0.001	71%

TABLE II. CORRELATION COEFFICIENTS, ORDERED BY STRENGTH, FOR K=7

we are able to date paintings within 15 years in 71% of cases. Whilst this result is not yet good enough to be of use to the art history world, it is promising.

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

We have also investigated the utility of incorporating expert knowledge within our framework. For each year represented in our collection we asked Dr Paul Joyner, of the National Library of Wales, to choose the one painting which best represents the artist's work for that year. Dr Joyner is a member of the Trustees of the Kyffin Williams Estate and he has written widely on Welsh Art and Kyffin Williams. These chosen paintings we consider to be connoisseurially/artistically selected exemplars (*artistic exemplars*, for short), which we can then use as a representation of that particular year.

The data on artistic exemplars opens up the options for different methods of classification. Rather than using K-nearest neighbour to classify each point in the feature space, we take the year of the nearest exemplar, and assign that year to the painting in question. If these exemplars are indeed indicative of the artists' output for that year, they should prove to be useful *anchors* in our feature spaces. To compare with this, we can also determine *statistical exemplars* either by using the centroid in feature space for a particular year (which provides us with a point in feature space which will not correspond to an actual painting), or the nearest actual painting to the feature space centroid for a year. The former technique does not, strictly speaking, give us an exemplar; the latter chooses as exemplar the painting which best represents a particular year according to a particular feature space.

Our intuition – that using artistically chosen exemplars could help us to exploit knowledge about the way the paintings change over time – turned out to be incorrect; results for Gabor filters with 4 orientations (the best performing method in our previous experiment) are shown in Table III. Results for the other feature spaces show a similar pattern, the same distance measure (χ^2) has been used throughout.

These exemplars give an interesting insight into the feature space. The paintings shown in Figures 1 and 2 are both artistic exemplars, however the earlier painting "*Snowdon, the Traeth and the Frightened Horse*", from 1948, is far from the feature space centroid for that year, whereas the later painting is very close to the feature space centroid for 1985. A visualisation

Technique	r	$P(r)$	$C(15)$
Artistic Exemplars	0.328	<0.001	57%
Statistical Exemplars	0.383	<0.001	61%
Centroid	0.403	<0.001	64%

TABLE III. CORRELATION COEFFICIENTS, ORDERED BY STRENGTH, FOR EXEMPLARS

of artistic exemplars and their corresponding statistical representations is given in Figure 7. From this you can see that artistic information does not necessarily correspond well to the feature space(s) we use. Note that whilst Figure 7 uses the feature space defined by Gabor filters with 4 orientations, our best performing: the pattern is similar for all other feature spaces.

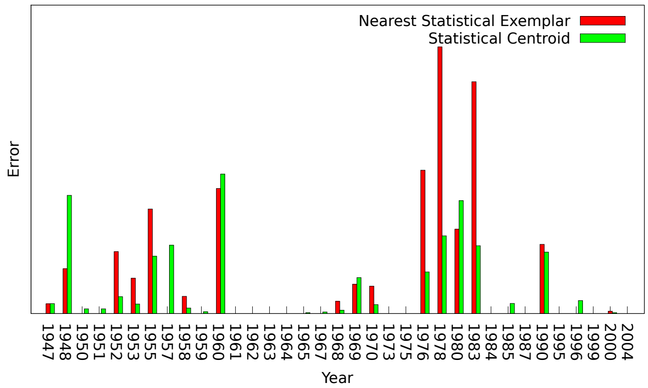

Fig. 7. Distance in feature space from artistic to statistic exemplars (red); distance from artistic exemplar to centroid (green). Lower values indicate that the artistic exemplar is near to the mean painting for a particular year, higher values that an artistic exemplar painting is an outlier for this particular feature space

VIII. CONCLUSIONS AND FUTURE DIRECTIONS

To the best of our knowledge this is the first work that attempts to date work by an artist by year. Similarly, we believe we are the first to try and perform digital analysis of paintings from a range of catalogue and web images.

The results presented here show that computer vision *can* help with the job of dating art within an artist's body of work. We are able to show strong, statistically significant correlations between our method's allocation of year and the actual year of painting; we are also able to classify 70% of paintings to within their actual year of painting (within a dataset that spans 6 decades). These results are not yet of great use to art historians, but we are hopeful that future work will be able to improve upon this. Several statistical avenues remain to be explored: we will look into feature combination and selection, and also investigate the potential for treating the year classification problem not as a nearest neighbour problem, but as an ordinal regression problem.

Future directions will also involve testing the methods presented here on the works of other artists who have shown great stylistic variation over the course of their career: we would like to build a dataset of, for example, David Hockney works. Whilst we have not yet performed this test we are hopeful of success: by avoiding brushstroke detection (which we expect to be artist specific) we hope to have developed techniques with application across a broader range of artistic styles, and by building techniques which work on catalogue images rather than those captured in controlled conditions, we are open to working with paintings from a wider range of artists.

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