Digital Analysis of Paintings

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***Abstract*—**

I. Introduction

Digital image processing is a field which encourages the crossover of different scientific disciplines, often biological research and computer vision align to automate the collection and analysis of plant growth. However, art and computing are fields which, at first glance, have very little in common.

But a deeper look unveils a plethora of different avenues from detecting forgeries to being able to date an artists work within a catalogue of their known pieces.

This survey paper will unearth some techniques which can be applied to the digital analysis of paintings, as well as existing research which has already applied computer vision to the field of art.

II. Colour Analysis

Digital images are typically considered to be a matrix of pixels, where each pixel contains information about the colour of that place in the image.

Colours can be represented in numerous different ways, but are typically three to four bytes; for example the Red, Green, Blue (RGB) colour space uses one byte for the levels of red, one for green and one for blue. The fourth byte is unlikely to be considered in artwork as it usually represents the transparency, known as the alpha channel, of the pixel.

A single byte colour space purely focuses on the intensity of a pixel, in actuality this represents a grayscale image.

Analysing colour is the base of all analysis techniques in image processing, the value(s) of a pixel with regards to its location and neighbours can be used to build up some very complex knowledge about the image. This section will deal specifically with the colours which an artist uses within their work, such as looking at the distribution of colours across a work, rather than using colour information to determine textures.

A. Colour Distribution

The distribution of colour across an image can give a surprising amount of information about that image, especially given that colour is very subjective to an individual.

Ivonna, Stanchev and Dimitrov investigated the colour distribution within the works of over 100 artists for several different countries and periods, using a system named Art Painting Image Color Semantics (APICSS)[1].

Existing systems already statistically analysed colours within an image and some even used classifiers, typically a naive Bayesian classifier as it fits well with statical methods, to perform extra analysis.

Unlike these existing system, APICSS focused primarily on the Hue, Saturation, Luminance (HSL) colour space as it is the closest representation to an artist's colour wheel. Hue, Saturation, Value (HSV) was also considered, but because the lightness is not symmetrical within the HSV colour space, it is less useful for direct comparison.

As with any system involving classification, a feature space is needed to represent an item within the data set. In the case of APICSS the feature space is three dimensional, one for each of the values in the colour space.

From this, a distance measure (in this case Euclidean distance) can be used to compare different items.

APICSS also take into account some of the metadata attached to each painting, such as the movement and sub-movement during which the painting was created. This allows for more statistical analyses to be performed on sub-sets of the data set.

APICSS appears to be a good system, which considers both metadata and analysis gained from the digitisation of artwork. The paper considers a wide range of artists and periods.

However, the use of a lossy image format (JPEG) could potentially skew the results. The system itself is very basic, especially if it only considers HSL and metadata. This is further compounded by only considering thirteen colours within the Hue (twelve separate colours and one achromatic).

Despite having a decent sized data set overall, some of the categories have relatively small items within them.

Overall APICSS is a good application of existing research, but uses very basic analysis techniques on the images themselves.

B. Pigment Mapping

Colour analysis can also give a glimpse into the colour pigments the artist used to create the work. Using a database of known oil pigments and *a priori* knowledge, it is possible to work out which pigments are used in a painting, and also to be able to show which parts of the painting are made up from which pigment[2].

This is done through a process known a multispectral imaging, the process of capturing a different frequencies to provide a different spectrum of light and enable more analysis.

This technique is especially powerful for segmenting different pigments in an image as each pigment is made up of a different substance.

Because this process requires both hardware and software it make a large different whether the materials a work is made up of are known. When known it can be possible to find the combinations of these materials at a given point and their concentrations.

When the materials are unknown, extra processing is required to decide which materials the painting comprises of. This process uses spectral processing but also requires prior knowledge of the artist and art tools.

In the experimental results this paper provides, the latter is achieved by a study of another of Van Gogh's works from the same time.

Pigment mapping across every pixel is a costly operation in terms of memory and CPU time. This research makes a reasonable assumption that a similar colour will have been painted using similar pigments to reduce the amount of pigment mapping which occurs. This does lead to unwanted side-effects, but the only way to combat these is to increase the number of pixels which pixel-mapping.

To reduce the number of pixels considered for pigment mapping the image is first partitioned into a number of smaller images to reduce processing time on the next steps

Each of these partitioned regions is then split into a number of clusters based on the colours of the pixels. This was done using supervised and unsupervised algorithms. The unsupervised algorithm was very sensitive and had long running times whilst the supervised algorithm requires a human observer.

Finally pixels within these clusters were then selected based on the similarity of pixels within the cluster, the clusters and partitioned images can then be stitched back together and rendered based on the pigment maps.

This research could be incredibly useful if it could be applied to the analysis of artwork and the field of multispectral analysis has already had a lot of success in other fields.

However, because this is both a hardware- and software-based system, it may not be something which can be used with regularity as it requires the physical presence of the paintings, which not all artwork analysis researchers have access to.

It also requires a lot of a priori knowledge of the artist and calculating the materials a painting consists of may be a difficult, if not impossible task, depending on the artist.

In conclusion, this technique can provide a very powerful analysis of a painting, but at the cost of requiring specialised hardware, the physical painting and expert knowledge about the artist, so is a very manual process.

This technique could be improved by using a less naive clustering unsupervised algorithm to remove some of the need for human intervention, but the need for the physical painting will always be a limiting factor of this work.

C. Difference Visualisation

Another approach to colour is to visualise the difference between two or more different images, this is particularly of use for comparing different versions of the same image - the original to a famous forgery, for example.

Image fusion is the process of combining two different images and has recently been applied to artwork[3]. In this research, a technique for showing the differences between two or more images which can show positive, negative and zero difference between the images, whilst maintaining regions of interest between the two images.

The method for doing this uses the CIELAB colour space, which maps more faithfully to human vision than other colour spaces. However, because of the limitations displaying the images, they are converted to HSV before they are displayed.

A hue for both the positive and negative difference values is selected by the user as a vector, then the difference in the HSV saturation of the two images is then computed into CIELAB, where it is an angle between the aforementioned colour vector.

Finally this is converted into HSV, where the Hue represents the sign of the computed image, the saturation the absolute distance and the value the average value of intensities of the compared image at that pixel.

The authors claim this fusion improves the comprehension of the difference visualisation of images and that it makes identifying regions of interest faster and more precise, but provide no experimental results to prove this other than the fused image result of four different copies of the same artwork.

This does keep the original image intact (albeit in grayscale with differences highlighted).

This does only provide visualisation rather than analysis, but could potential be used as part of a larger system to build more complex analysis techniques. This might be especially useful to pick up difference between an original and a derivative work or forgery.

At current, the images must be aligned and scaled manually, but this process could be automated trivially.

This research appears to be of very limited use, but when used within as a part of a larger system could provide some very interesting analysis which could be used to train classifiers to detect forgeries, etc. but this still has limited scope.

III. Texture Analysis

Paintings are somewhat unlike the normal subject for image processing, whilst most images are either simple two dimensional images, or two dimensional slices of a three dimensional object. Paintings often thought of as two dimensional, but with many paint types these paintings become three dimensional.

This aspect is lost in the digitisation of the painting; but there are still ways of analysing the texture of the image by analysing the colour of the image. Quite often, this is as effective on a one dimensional colour space as it is on a three dimensional one.

Filters can be passed over an image to gather basic information such as direction of lines within the paintings. More complex techniques for analysing texture involve using wavelets and considering nearby pixels.

A. Steerable Filters

For techniques which involve applying a filter to decide the direction of a line within a picture, one often needs to be able to change or rotate the filter by varying amounts of degrees. This principal is often described as steering a filter and an efficient technique for doing so is described in [4] in both two and three dimensional space.

This technique involves finding a function of x and y which steers a filter

B. Gabor Filters

C. Histograms of Edge Orientated Gradients

A method for analysing the texture over an image to to create a histogram which contains the orientation of all the gradients over an image. This technique has been applied to the field of human detection[5], but is also useful when applied to the realm of digital analysis of artwork as well.

A lot of the methodology for human detection involves the normalisation and classification, but does include some useful information about the practises of generating histograms of edge-orientated gradients. The gradients are computed using a variety of discrete derivative masks combined with degrees of Gaussian smoothing, although the results show that Gaussian smoothing and larger masks damage the performance.

Each pixel is then binned according to a weighted vote from the mask, then each vote is accumulated into orientation bins in local regions, which could be rectangular or radial.

These orientation bins were evenly spaced across $0 - \pi$ unsigned bins or $i - 2\pi$ signed bins. This is significant to note an orientation θ below π is often thought of as equivalent to $\theta + \pi$ in image processing.

Normalisation is then applied to reduce the effects of local contrast and is good for performance in the field of human detection. For artwork this may be less useful as these features are of importance.

This research shows very good experimental results of large, popular data sets and beats all of the existing techniques on false positives (although no data for false negatives is shown).

Although this research does not directly relate to the field of digital analysis of artwork, it has been used to generate some interesting analysis[6] although not all of the technique was applied in that research.

The use of this research is the ability to store orientation data in histograms, which are very easy to process digitally.

In conclusion, this technique provides a powerful analysis technique and the experimental results on several decent sized data sets to prove this. Although not all of the technique is useful or applicable to the digital analysis of paintings, the parts which are have been successfully used in research into artwork.

D. Multifractal Classification

Another analysis paradigm is fractal geometry which is based on the idea that all analysis performed on an image at difference scales are equally important and that the richest information can be found in the mechanisms which relate them to one another.

Because of this, fractal tools can be used to analyse contours and textures of images.

Multifractal analysis concentrates on the use of processing tools which describe the fluctuations within regular regions of an object which at different scales.

Until recently multifractal analysis was rarely applied to image processing problems, but with the breakthrough in an efficient formulation of multifractal analysis obtained through wavelet leaders.

The use of wavelet leader multifractal analysis has been used to explore painting texture classification[7].

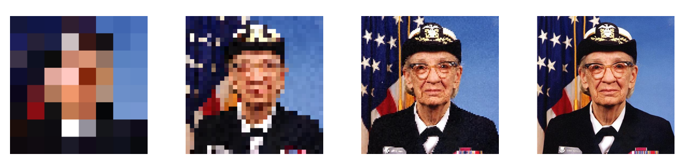
Image processing is a field which has grown out of signal processing; an image can actually be thought of as a two-dimensional signal, which allows existing signal processing techniques to be applied to them. In early days of image processing the Fourier transform was often used to decompose images into signals. In more recent years wavelets and transforms using wavelets have become more popular, as they can provide all the features of a Fourier transform, but also provide localised time information, as well as localised frequency information.

In the case of images, localised time information maps to the location within an image.

In this research, a 2D discrete wavelet transform is applied to the image to gather the wavelets coefficients, normalising the image to the correct form needed for the definition of wavelet leaders.

These coefficients enable a definition of the global regularity of the image.

To allow image classification across different scales, one needs a dyadic space; a space in which there are a collection of regions of different scales, where a region at one scale can also be viewed as the union of regions in a smaller scale. Figure 1[1] shows an example of this where the large regions show only a pixalated view of the image and the smallest the individual pixels of the image.



(a) $C = 8$ (b) $C = 32$ (c) $C = 128$ (d) $C = 512$ (Original Size)

Fig. 1. Example of dyadic space using an image of Grace Hopper (512x512 pixels) at different dyadic scales (C), note how the picture becomes less pixalated at higher scales

[1]The photograph is property of the U.S. Federal Government, and is therefore in the public domain

A natural interpretation of multifractal analysis needs to be based on wavelet leaders, which allows an estimation of the multifractal spectrum of an image. The wavelet coefficients at finer scales within a small neighbourhood are used to renormalise the wavelet coefficients at a given scale.

This is all theoretically very sound, but in practise it cannot be used on paintings without some modifications, mainly due to the fact that digital objects do not have an infinite resolution. So the analysis is slightly simplified to account for this to provide a fair estimation of the real analysis.

This technique was applied to several different works, but the most interesting of there was the Princeton experiment, where an artist produced seven distinct small paintings using different materials. Two weeks later the artist was asked to produce replicas as close to the original as possible.

Both the originals and replicas were scanned at a very high resolution to allow this analysis to be as detailed as possible.

The results showed that, systematically, the textures of the replicas were globally more regular and smoother than the originals. However, it should be noted that getting these results required the expert selection of sections to analyse and the a posteriori selection of the range of scales for wavelet leaders.

With promising results shown from this experimentation, attention was turned to a norm for painting analysis: Van Gogh. Rather than consider the global state of the canvas, each image was split into smaller sections for the analysis, as paintings very rarely have the same texture globally.

This analysis was used to try and place paintings in a date region and detect forgeries. The results shown for dating paintings into a period show some promising results, where the majority of paintings were correctly clustered into their correct periods. For detecting forgeries the results are promising, but one forgery slips by when it was noticed by experts.

This technique is agnostic to the colour space and the authors do apply it to several different colour spaces, including black-white intensity, RGB and HSL.

There is a lot of expert knowledge which cannot be automated or, where it can be, is very arbitrary such as blindly selecting patches.

The results from the Princeton experiments are promising, but the results are very sensitive to the material of the canvas as well as the tools used, whilst this might be use for detecting forgeries, there might be situations where this isn't desired.

The images the authors use are high resolution (800 DPI) and they note that a lower resolution makes it difficult to decide on the range of scales which are involved.

The data sets used are relatively small and, although they increase the knowledge by taking multiple patches from the Van Gogh paintings, but for the results they show only individual paintings are considered. One could easily question the validity of their results based on this.

In conclusion this is a very complex but powerful technique which is actually applying theoretical concepts to perform some interesting analysis and classification. However, the sensitivity of the technique and with the need for expert and a posteriori decisions do limit the real application of this research.

E. Texton-Based Analysis

Analysis of texture can also be performed with the help of a set of small patches, or textons, relating to the texture of the image. An interesting approach is to learn a variety of these textons from example images and then look at a histogram of the frequencies of these textons on the images to classify[8].

Segmentation of brushstrokes is, understandably, difficult - especially digitally where the image is usually only two dimensional, but one can consider the texture of the painting with more ease and can provide a good insight into the artists style.

Filters are becoming less popular for painting analysis as the filter often normalises the image to a certain extent in the process of analysis. Other approaches like wavelets and pixel-based representations, such as texton approaches, are becoming more popular to avoid this issue.

It should be noted that whilst textons are a building block of the text of an image, they are not identical to brushstrokes.

To construct the codebook of textons, 5000 patches are selected in random locations from each painting in the training set. These patches are then clustered and the most exemplary patch (the central patch) is selected as the most representative for that cluster.

From this codebook it is then possible to generate a histogram for any image which estimates the distribution of these textons across the image. The histogram is created by applying a sliding window across the painting and selecting the nearest texton in euclidean space to the window. Finally the histogram is normalised to sum up to 1.

The authors note that these histograms could be built up for different sizes of textons to increase the feature space available for analysis, for their own experiments they use six different scales of texton.

Because the aim of this research was to work closely with experts in the field, the authors also came up with a method for visualising this information. For an image processing system this may not be required, but could be used to extract more useful information from the analysis.

Because of the high dimension space it is necessary to reduce the dimensionality of the results to allow it to be human readable. Usually this would be performed by Principal Component Analysis (PCA), but the way in which the data is structured, PCA is too lossy for texton histograms; it has a linear nature whist the texton histograms may be high-dimensionally non-linear and it focuses on preserving the global structure rather than local structure of high-dimensional points.

There are other techniques which might have been applied to solve these problems, but the authors found some shortcomings with these techniques which would have made real-life visualisation difficult.

To cope with this, a new method for dimensionality reduction was invented: t-Distributed Stochastic Neighbor Embedding (t-SNE). This method hinges around keeping the conditional probabilities between the high and low dimension spaces similar.

Interestingly, in the experiments PCA was first use to reduce the dimensions down to 50, and then t-SNE was used to reduce down to two dimensions. Suggesting that, for very high dimensions, t-SNE is not very effective.

The results on 117 high-resolution grayscale Van Gogh paintings show that most of the non-Van Gogh paintings appear on the peripheries of the visualised two-dimensional graph, apart from two specific forgeries: the Wacker forgery which had fooled experts for many years, but can successfully be found by looking at global features. The other, created by Gaugin, may remain undetected for the same reason.

Visualisation of dated Van Gogh work does show some difference between the two time periods considered, but not enough to cluster or classify upon with any degree of accuracy.

This approach is definitely a useful one, especially given that the textons are learned from existing work, making analyses such as trying to date an artists work from sets of his known work very applicable. Although colour and global features are not considered by the textons described in this work, colour would be a simplistic feature to add and global features could be part of a separate technique which is later included with the histogram.

The paper does leave some answered question, one notable one is how best to decide the number of clusters to build the texton histogram from and which scales the textons work best at. For use by experts with t-SNE applied this might be some useful work, but t-SNE seem to have limited application outside this form of data set. A comparison between PCA and t-SNE would, perhaps, show the advantage of the latter and an explanation as to why PCA was applied before t-SNE on their own experimental results would help others to better apply such methods correctly.

IV. Statistical Analysis

A lot of analysis can be gained from passing filters over an image and considering the colours used. However, a lot of these depend on some way of statistically analysing the results. This section will look at some of the research that considers some of the more statistical elements to provide analysis.

Whilst gaining results of analysis techniques, it is also important to be able to interpret them digitally for some form of use; determining whether a painting is authentic or not, or dating an artist's work within a set of their known work.

Often these techniques involve using a form of machine learning to gather meaningful data from the high dimensional feature space which image processing processes provide.

A. Stylistic Analysis

All artists have a distinguishing style which may change as their career progresses. Art historians find this a challenging problem as many factors of the painting need to be taken into account. Image processing and machine learning techniques can be used to aid this process.

Stylometry, the study of an artists style, has many problems involved with it. Two of these are: extracting distinguishing features and dating a painting, both these problems are tackled in [9].

This research uses considers the artists style to be a hidden variable which controls the observable properties of the image; the colour, brushstrokes, etc.

The dating challenge is the act of dating a painting from a catalogue of known paintings from the artists lifetime. An artists style is likely to change over time, especially as they meet their peers and try out new movements.

This research considers how a human expert might approach the problem of determining style and that paintings may degrade over time due to the materials used to create them. Historians must combine a potentially noisy observation with pre-existing knowledge to come up with an analysis of the style.

Computer systems have to use features of an image, considering both global and local information, to build up a high-dimensional feature space which can then have statistical analysis performed upon it to gauge some information about style.

It has already been discussed that a HSL colour space provides a more representative view of an image than a RGB space. However, HSL does not exist in a Cartesian space. This can be achieved by transforming the HSL space into an XYZ space by "unrolling" the radial elements of HSL.

As with many techniques which utilise wavelet transforms, a very high resolution is used to gather information which may be too fine for a human eye to perceive. A dual-tree complex wavelet transform using the aforementioned XYZ colour space can detect colour patterns as well as local difference.

These wavelets provide coefficients in very high dimensional space which a large amount of noise. To deal with this there is a need for dimensionality reduction and normalisation of noise within the feature space.

Hidden Markov Trees provide an image model over numerous different resolutions. They act like Hidden Markov Models but also considers a tree like structure which maps to dyadic space. This allows for an image to be described as a statistical entity rather than a set of pixels.

At each scale there are hidden variables which control the wavelet coefficients. These hidden variable represent either a smooth region, which has a small variance, or an edge, which has a large variance.

The images are split into several patches to allow the analysis to be performed effectively.

Results for the dating challenge, 66 Van Gogh paintings were used with the goal of dating three test images which cannot be easily dated by art historians. Training was performed on the set of paintings using 10-fold cross-validation using several different classifiers. The best classifier; random forest; had a generalisation performance of 73.7% and the results from the three test images aligned with the conclusions of the art historians, but this is somewhat conjecture as the dates aren't officially known.

Extraction distinguishing features focused on extracting flowers within the paintings. Irrelevant patches were removed from the training images and again training was performed using 10-fold cross-validation using several classifiers. Once again random forest was the best decision and several distinct distinguishing features.

The results of this research do seem promising, and the techniques described here do seem like they can provide some very powerful analysis.

The sample size is a little small, but the split into different patches allows for a larger number of samples for training. Though this still only has a certain number of date ranges to work with.

The size of the patches is never fully explored and the research blindly uses 256×256 pixels for each region. It would be interesting to see what effect changing the size of these regions would make upon the research.

In conclusion this research provides some very powerful analysis with the experimental results to back it up in two different fields of stylometry which agree with expert opinion and begin to bring forth some new ideas.

B. Authentication of Artwork

Another interesting problem within the field of art analysis is the problem of many hands; that is determining how many authors created a work and which parts of said work can be attributed to which author. Obviously, the latter can also be simplified to test which artist created a work and thus detecting forgeries.

One attempt to attempt to solve the many hands problem is described in [10]. As with much of the recent work into applying image processing to artwork, it considers paintings at multiple resolutions and orientations using wavelets.

The method for this technique is to decompose the image using wavelets. In this paper quadrature mirror filters; filters which split an input signal into two bands; are used to split the frequency space into multiple scales and orientations. This produces a statistical model at each scale and orientation; known as a subband.

The optimally predictive set of neighbours is selecting by minimising the prediction error using a brute force iterative approach on a per-subband and per-image basis across all subbands.

Additional statistics are also gathered from the errors of the final predictor, again for each subband. For n levels of decomposition, this will produces $24(n-2)$ values ($12(n-2)$ for optimal predictors, $12(n-2)$ for error statistics).

These large dimensional spaces can be projected into a human-friendly subspace using a process named Multidimensional Scaling (MDS). MDS attempts to maintain the distance between data points when projecting into a lower dimensional space so should still provide a decent visualisation of the higher dimensional space.

The first experiment focused on authenticating the work of Pieter Brugel the Elder who used very distinct style which the authors felt would be especially applicable to their technique. A set of 13 paintings conprising of 8 authentic Brugels and 5 famous imitations was the subject for this analysis.

Each painting was scanned in very high resolution and was separated into 64 non-overlapping regions. Each subimage was transformed the proposed wavelet transform at five levels and three orientations producing a 72 dimensional space. Authentication was performed by applying Hausdorff distance to this space with the assumption that authentic paintings would be closer together.

This these experimental results it did indeed show that this was the case and are statistically significant, even in a reduced feature space through dimensionality reduction.

This was also to applied to a painting by Pietro di Cristoforo Vannucci (Perugino) which is disputed by art historians to have been produced by more than a single artists, which, during the Renaissance was common amoungst the great works.

This effect is commonly observed in the six faces which are depicted in this painting. These faces were first selected and then partitioned into 256×256 regions as with the Brugel work. The technique was then applied and Hausdorff distance was measured between the feature spaces. Viewing the results shows an obvious clustering of three of the faces, whilst the other three are completely separate from this cluster and from each other. This would suggest that there were at least four hands involved in the painting, which is consistent of the views of some art historians.

The sample size both experiments were performed on is relatively tiny when compared to other studies using similar techniques. One could easily question the validity of such results, especially with the subjectivity of the second experiment where there is no definitive answer.

The work of Brugel is noted to have delicate lines and shading which was expected and shown to have good results. A cynical reader might infer that this analysis technique is therefore not suited to other styles of art.

It's also interesting that the Brugel paintings were cropped to a given size before being split into regions as this would surely lead to loss of information when it might have been better to just increase the number of regions across the image to include the whole image.

As with other research including wavelets the dependence on a region size of 256×256 pixels is notable. This appears to be a standardised size for the application of wavelets, but there appears to be no documentation of this.

In conclusion this work presents a method which may provide an insight into how many authors a work has, but has very few experimental results to back up this claim. Especially given other research into similar areas.

C. Dating an Artist's Work

V. Brushstroke Analysis

The ideal technique for analysing a painting digitally is to be able to extract brushstrokes from the painting and be able to analyse them based on their shape, colour and where on the painting different types of stroke were made.

This is a very difficult task, it may be easy for a human non-expert to view a painting and roughly estimate where the surface brushstrokes are, implying that an expert may be able to tell far more from a detailed view of the painting, including multispectral imaging using X-rays.

For a computer to do this is a very intensive and complex task. As discussed in section III is can be easy to view the texture of an image and even to be able to pull out some information about the texture of brushstrokes. But actually segmenting these brushstrokes for extraction quickly is a different story.

This section will look into some of the research which has been attempting to extract brushstrokes from paintings for the purposes of identification and authentication of artwork. However, because this field is relatively narrow, some exploration into extraction of brushstrokes in calligraphy will also be considered as the fields have some overlap.

A. Artistic Identification

To be able to extract brushstrokes it is important to understand how an expert might go about the task. A lot of analysis techniques tend to be inspired from how a human might go about the task, this also help a human to understand how the process was gone about and may give extra meaning to the results.

There is a lot of knowledge to be gained from looking at the expert process, and this knowledge can be applied to reduce noise and parameters from the extraction process. The knowledge of painting materials, the state of the preservation of the painting and the working methods of the artist themselves.

Interestingly, this leads to the conclusion that parts of the painting should actually be discounted from the analysis, elements which have deteriorated over time due to instabilities in the painting materials or the lack of preservation of the painting leads to what most computer vision researchers would call "noise". Certain areas of the painting may not have been painting by the artist's hand, such as cracks in the painting from the drying process, need to be considered here.

It seems that it should be far more important to look at the areas where brushstrokes were obviously painting "rhythmically": a series of fast strokes arranged in a certain pattern, which can then be used to build up a personal handwriting for a given artist[11].

Three different two-dimesnional wavelet transformation techniques were used in this research:

- Penn State
- Princeton
- Maatrich

Penn State is an orthonormal series generated by a wavelet, implemented using fast subband filtering, critically sampling the data.

Princeton forgoes critical sampling in favour of greater orientations using complex wavelets.

Maatrich uses Gabor wavelets to provide a similar range of orientation selectivity as Princeton, but in a way which is closer to a physiological templates.

Because of the differences between these wavelet transforms, different classifiers need to be applied to the resulting coefficients.

Both Penn State and Princeton transforms can use a hidden Markov model approach. Because Markov models have states which are linked to the predecessor or neighbour states with a probability distribution. Hidden Markov models are Markov models where this probability distribution is unknown and can be inferred from the data which constructs the model.

There are several classifiers which can be applied to Markov models, although typically these relate to some form of expectation maximisation technique.

All experimental results were gathered from a data set containing 101 paintings in the style of Van Gogh. 82 of which are believed to be true Van Gogh works, 13 which are currently in dispute and 6 which are known imitations. All of these paintings are scaled using the same technique to be equivalent sizes.

The approach for using Penn State was to gather several unquestionably Van Gogh paintings which are representative of his style (exemplar images) as a training set. By not including negative examples in the training set the resulting classifier is more stringent.

The paintings are then divided into patches of roughly 512×512 pixels such that all the patches from the same painting are the same size. Dissimilarity measures between these patches are calculated using both texture- and stroke-based features. Paintings are then compared using the aggregated distances between the patches of the images.

Texture features were extracted in a form which shows the abruptness of changes in variations at different orientations. Textures were only captured at the highest scale. These are then put into a feature vector which can be converted into a Markov model.

For extraction of strokes an edge-detection algorithm is used to detect contours of the image, which can then have several geometric features computed, such length, average curvature and orientation.

Because textures are dependent on their neighbours it is sensible to build up a probabilistic model, namely a Markov model, to show these dependencies. Because the probabilities which affect the dependencies are unknown this must therefore be a hidden Markov model, using two dimension (as images are two-dimensional). A likelihood classifier can then be trained from the training set and applied to other 2D hidden Markov models to be able to classify examples.

Spatial features are less important for brushstrokes as they capture more global information rather than information which is likely to be affected by neighbouring strokes. Clustering can be applied to this to partition the data set then new examples can be classified using the distances to these clusters.

Princeton shows the scale at which details start to emerge; each patch is analysed using the wavelet transform and then these coefficients are stored is a hidden Markov tree in a similar process to [9], where the hidden states take the form of edge or non-edge. This helps show the scale at which an individual artist's style emerges as the transitions between edge and non-edge will occur at different scales.

Only 79 of all 101 paintings were analysed by Princeton, the other paintings were too dark for meaningful analysis to be gained from them in this experiment. 65 of these were van Goghs, 6 imitations and 5 of the questioned paintings.

MDS is used to find an arrangement of all the points in a three dimensional space (as opposed to the very high dimensional space the hidden Markov tree uses. For all van Gogh paintings the centre point is determined, where all of these paintings are equally weighted.

The 3D visualisation shows a good separation of the van Goghs from the non-van Goghs, but to be able to truly use this, a radius classifier is applied such that a lower radius is more likely to classify as a van Gogh and visa versa. An appropriate point r is chosen as the cut distance at which the label changes, such at van Gogh paintings are closer to the centre than r.

This classifier was tested using leave-one-out cross validation; a validation technique based on k-fold cross validation where k is the size of the data set. k-fold cross validation partitions the data set into k subsets. Each subset has classification performed on its elements based on training from the other subsets.

Leave-one-out cross validation is a useful cross-validation technique for small data sets and can be used to gather a correlation of expected output against classified result. This can also be used to gather the statistical significance of the results.

Biologically inspired techniques have shown promising in other fields of computer science, notably items like Artificial Neural Networks, Immune and Endocrine Systems; Swarm Intelligence such as Ant Colony Optimisation; etc.

Using the human visual system as a metaphor paintings can be analysed using three principals: 1) Importance of contours; 2) Analysis at multiple scales; 3) Similarities are reflected in local textures.

The Maatrich transform uses Gabor wavelet filters at multiple scales and orientations. The provides an "energy" value for each pixel, orientation and scale. These values can then be binned into a high-dimensional histogram. This allows a Support Vector Machine (SVM) to be trained and new example to be classified with. Because there are only two states (van Gogh and non-van Gogh), a SVM is a good classifier. Again, leave-one-out cross-validation is used for each painting, the patches are separately classified then the most frequently returned label is used to classify the painting.

Penn State begins to show some good results, although one of the imitations is considered to be one of the five closest to the training set of 23 van Goghs.

The radius classifier applied to the Princeton tranformation successfully classified 55 of 65 van Goghs and 9 out of 11 non-van Goghs correctly. At even finer scale shows even better results.

Maatrich transforms with a SVM classifier successfully classified four of the six non-van Goghs correctly, but wrongly classifying two of the van Goghs. This starts to show that it can detect dissimilarities in the brushstroke texture of a painting, but that some difference may be too subtle to pick up.

The use of leave-one-out cross-validation means the experimental results are very valid; but the lack of significance does remove some of this validity - it is up for debate whether a null hypothesis could also be to play.

The images are high resolution greyscale, so although colour information has been lost but the resolution means that most of the paintings should be uniform and detailed.

The discussion and use of expert knowledge means that the results gained are potentially more valid by not considering several sections of a painting. However, the opposite argument could be made that part of van Goghs style was to deform the paintings slight by leaning against them, etc. and therefore is a better indicator of his style than some of the brushstrokes.

This does show positive results and the techniques are well thought out, including discussions of other classifiers which could have been used.

As is a common problem in brushstroke extraction there is no ground truth on which these techniques can be applied to, so it is difficult to know how well these techniques will apply to other paintings by van Gogh or by different artists.

In conclusion, this is a decent application of existing research with real results being gained, although it doesn't deal with the extraction of brushstrokes formally it is a good step in the right direction.

B. Rhythmic Brushstrokes

Using computer vision to segment brushstrokes is a difficult task; often requiring expert knowledge of the painter and manual intervention to enable the process. [12] shows a method for the automatic extraction of brushstrokes.

This method involves a complex process; first the image has an edge detection algorithm applied to it, then these edges are pruned to remove noisy, short and unconnected edges to improve the actual segmentation of strokes.

Because an edge detector doesn't always pick up the full brushstroke, any gaps in the painting are enclosed using a greedy process of scanning neighbours and linking the nearest via a straight line if they are within a certain distance.

Any fully enclosed brushstrokes are then extracted and checked against an upper and lower threshold for size. These thresholds were pre-selected to give a good estimate for the size of a brushstroke. This is finally labelled a brushstroke if the backbone is not too branched, it has a reasonable ratio of broadness to length and the size of the stroke is proportional to the backbone of the stroke.

After this process is complete, the image is then segmented with regard to colour (RGB) and directions (horizontal and vertical). k-means clustering is then applied multiple times, gradually decreasing the threshold for the average distance in the cluster. Any sufficiently small clusters are removed at each step and are not considered in the future runs of the k-means algorithm. This process is done to remove any noisy components there might be in the digitisation of the image.

Brushstrokes which are already labelled are then removed and any remaining clusters are labelled according to the same process.

C. Stroke Decomposition

D. Calligraphy Stroke Extraction

VI. Conclusions and Summary

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