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

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[4], 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[5] 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

E. Texton-Based Analysis

IV. STATISTICAL ANALYSIS

A. Stylistic Analysis

B. Authentication of Artwork

C. Dating an Artist's Work

V. BRUSHSTROKE ANALYSIS

A. Artistic Identification

B. Rhythmic Brushstrokes

REFERENCES

[1] K. Ivanova, P. L. Stanchev, and B. Dimitrov, "Analysis of the distributions of color characteristics in art painting images," *Serdica Journal of Computing*, vol. 2, no. 2, pp. 111–136, 2008.

[2] Y. Zhao, R. S. Berns, L. A. Taplin, and J. Coddington, "An investigation of multispectral imaging for the mapping of pigments in paintings," in *Electronic Imaging 2008*. International Society for Optics and Photonics, 2008, pp. 681 007–681 007.

[3] J. Blazek, B. Zitova, and J. Flusser, "Image fusion for difference visualization in art analysis," in *Digital Heritage International Congress (DigitalHeritage), 2013*, vol. 1, Oct 2013, pp. 653–656.

[4] 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*, vol. 1, June 2005, pp. 886–893 vol. 1.

[5] A. Brown, G. Roderick, H. Dee, and L. Hughes, "Can we date an artist's work from catalogue photographs?" in *Image and Signal Processing and Analysis (ISPA), 2013 8th International Symposium on*, Sept 2013, pp. 558–563.