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A Novel Algorithm based on Contourlet Transform for Extracting Paint Features to Determine Drawing Style and Authorship

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Abstract

Objective: To develop a hybrid authentication method, Painting Authentication using Contourelet Transform (PAUCT), combining a contourlet transform algorithm with HMT-Fisher distance information for the purpose of art authentication based on the analysis of the background of paintings. **Methods/Statistical Analysis:** Methodology includes feature extraction from samples, as well as modeling using Hidden Markov tree and Fisher distance information. This is followed by validation against the work of the original artist through feature testing, with final output measured and validated using a variety of statistical methods to determine accuracy. **Findings: Application/Improvements:** The proposed model improves accuracy in detecting fake art, to 85% from 80% in current works, due to its applicability to discrete data which allows brushstroke analysis at different resolutions.

Keywords: Image Processing, Painting Analysis, Paintings Authentication, Painting Classification, Signal Processing

1. Introduction

Art scholars have been analyzing paintings for different purposes. It includes art authentication, classification, dating, appreciation and conservation. Developments in the field of science and technology, have led to the use of different algorithms from chemical and material sciences as the aiding tools to art scholars. For instance, dendrochronology and radiocarbon dating have been used for determining the age of work of art[1–4]. In order to determine the authenticity of work of art, scholars, use their expertise, study all the historic documents related to a particular artwork and use different scientific tools and algorithms as an aiding tool. However, different art scholars have different opinions. Due to this reason, a common ground is not reached and the authenticity of the painting is often disputed.

With the significant developments in computing power, digital image processing and artificial intelligence, the art world has begun to consider using computers in the analysis of paintings[5–8]. Different researchers have proposed different automated algorithms to determine the authenticity of paintings. This is despite the fact that different habitual algorithms of a painter are exhibited by the brushwork used by them in their paintings. For instance, it is known that the brush strokes of Van Gogh are distinct and visible. However, much shorter, delicate and lack edges in the case of Gauguin[9–12]. These brush strokes can be characterized quantitatively with the help of digital image processing tools for the purpose of

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painting authentication. The accuracy rate of some of these proposed algorithms are quite good. However, the desired higher accuracy rate is still not achieved using image processing and artificial intelligence algorithm. Therefore, a new algorithm of painting authentication that can overcome the limitations possessed by the current solutions is needed.

This paper aims to propose and implement a new hybrid algorithm for painting authentication. It is organized as follows: In section 2 we will be discussing different current solutions. Different impact factors will be discussed in section 3. The newly proposed hybrid algorithm along with the implementation result will be discussed in section 4, the results from the experiments will be discussed in section 5.

An algorithm for classification of paintings based on multifractal analysis of the homogeneous textures present in the digital images of the paintings[13,14]. The tools used from Empirical Mode Decomposition (EMD) for the purpose of measurement and comparison of the individual style of the artist[15]. Similarly, a novel dataset of digital paintings from 91 different artificial arts for categorization, style classification and saliency detection[16]. This algorithm was able to achieve the maximum accuracy of 60%. Likewise, the artistic similarity measured for the purpose of classification through a comparative study[17,18]. Another algorithm for classification of paintings based on color and textural features was tested on the collection of 500 images of paintings from different authors. This algorithm was able to get the accuracy rate of 75% which is an increment over the other algorithms[19].

Proposed an algorithm has proposed for painting authentication based on signal processing algorithms in combination with artificial intelligence algorithms[10]. It used Wavelet-Hidden-Markov-tree-based Fisher information distance as a metric of stylistic similarity between brushwork samples. This algorithm was able to achieve an accuracy rate of more than 86%. Similar algorithms using contourlet transform. This algorithm was also implemented using wavelet algorithms and results showed that the accuracy rate achieved using contourlet transform is higher[20,21]. Likewise the top probabilistic and wavelet model used for analysis of work of art[22,23]. The features are extracted using wavelet transform with Hidden Markov Tree (HMT) along with hierarchical clustering for the purpose of identification of stylistic keywords and the Bayesian model for learning stylistic patterns of keywords. However, this algorithm is unable to separate images if they are stylistically similar. For instance, both master and disciple tend to have the same stylistic behavior. It fails to identify the difference between those two.

An automatic algorithm developed for the recognition of an artistic genre in the digital reproduction of the paintings[6]. The features were extracted using 3D color histograms and Gabor Filter Energy. A new solution proposed using time-frequency analysis analyzing the weaves in canvas of the X-Ray photograph of the painting images[24,25]. This algorithm can be used for the purpose of dating of the painting, canvas forensics and identification of the canvas roll mate. The limitation of this algorithm is that, for counting the thread present in the canvas, the X-Ray images of the entire sample are necessary. It might not be feasible and available in all circumstances. Similarly, a noble algorithm proposed based on the graph theory[26,27]. The features retrieved using this algorithm was used for the purpose of authentication and classification. However, this algorithm works at its best only when there is significant difference in the lightening and scale between the paintings. A new algorithm proposed for the purpose of authenticating genuine Van Gogh paintings from forgeries[28]. The process was based on feature extraction followed by the detection of outliers using a geometric tight frame and simple statistics. This algorithm was able to gain a classification accuracy of 86.08%.

The analysis of the different existing solutions for painting authentication shows that solutions based on the signal processing with the use of artificial intelligence algorithms provide higher accuracy rate than the other algorithms[29–31]. Although, one of these algorithms proposed based on the graph theory is also able to achieve a similar rate of accuracy, it has not been widely tested and accepted. Due to this reason, this research will aim to overcome the limitations possessed by these algorithms. It aims to increase the accuracy of image authentication by proposing a hybrid solution based on signal processing and artificial intelligence. It also aims to increase the accuracy without affecting the time consumption of the existing solution.

2. Important Factors in this Work

Detailed analyses have been carried out in this work for all therelevant algorithms that tried to tackle that same problem. The analysis of this work is based on the main factors, such as accuracy, processing time and cost. The cost of detection of the forgery of a painting using computerization is negligible in comparison to the cost of using art scholars and other aiding tools. Similarly, among the existing solutions, cost does not play a significant role as all of the solutions are cost effective. Accuracy is the most important and significant factor. Analgorithm that has higher accuracy is more reliable and widely accepted. Hence a higher accuracy rate is always desired, but a 100% accurate algorithm is not available yet. The processing time is the second main factor in this work. It plays an important role in these algorithms. For instance, if an algorithm is 100% accurate but consumes an indefinite time, then the algorithm is of no use. Hence in our proposed algorithm, accuracy and time are the most important factors which are analyzedin this section.

However, the sample used in both of these solutions has different quality. For instance, high resolution grayscale ektachrome images have used[12], while the image sample used[20] was in tiff format and was taken by regular cameras. Similarly, a wavelet algorithm used and a curvelet algorithm used. It was also tested on a wavelet algorithm, but the result obtained using a contourlet algorithm was more accurate than using the wavelet algorithm. Similarly, the background patches used with the fisher distance algorithm have helped to increase the accuracy. Hence, our proposed hybrid solution will be using contourlet transform over wavelet transform along with background image patches and fisher distance information. Using these components will increase the accuracy rate of the authentication process.

2.1 Accuracy Analysis

The first main factor in this work is accuracy. Visual Stylometry using Background Selection and Wavelet-HMT-based Fisher Information Distances for Attribution and Dating of Impressionist Paintings (VSUBWHFID) that was proposed[12], and Stylometery of Paintings Using Hidden Markova Modeling of Contourlet Transforms (SPUHMMCT) that was proposed by[20] have been selected as the best solutions. We have found that VSUBWHFID has the highest accuracy rate of 86.35%, while SPUHMMCT has 83% as presented in Table 1. These results were found by testing many different images. All Images were classified against the sample data collected, and tested against the forged and similar paintings.

2.2 Time Consuption Analysis

Time is an important factor in determining the effectiveness of an algorithm. In VSUBWHFID, the extraction of background patches is necessary, which is the case in our proposed solution as well. It lengthens the manual process compared to the selection of regular image patches. Hence, for an automated algorithm of patch extraction determining if a patch is a background patch or not is necessary.

SPUHMMCT does not require any manual process. However, the background selection in the VSUBWHFID is a manual process, which makes VSUBWHFID more time consuming. However, the VSUBWHFID process has high accuracy over the SPUHMMCT as is shown in Table 1.

Table 1. VSUBWHFID and SPUHMMCT accuracy and processing time analysis

S.N	Method Name	Author	Accuracy		Processing time	
			Number of successful authentication	Accuracy Percentage	Is this method time consuming	Can manual step be automated
1	Stylometery of paintings using hidden Markovic modeling o f Contourlet Transforms(SPUHMMCT)	In [20]	39 out of 44 images in one data set and 28 out of 36 images in other data set.	83.75 %	N	-
2	Visual Stylometry using background selection and wavelet-HMT-based Fisher Information distances for attribution and dating of impressionist paintings(VSUBWHFID)	In [9,29]	57 / 64 in one dataset and , 55 / 65 in second data set.	86.82	Y	Y

3. Proposed Work

A new hybrid algorithm Painting Authentication using Contourelet Transform (PAUCT) is presented. The related algorithm, the components and detailed explanation are presented in this section.

3.1 PAUCT Stages

Our proposed PAUCT has four main stages. The first stage is features extraction using contourlet transform. The background of the paintings is selected in this stage and fed as input for the feature extraction process. The contourlet transform is used for this purpose. The samples are collected from the paintings of different artists, and usually from the popular inline libraries such as Google Arts.

Modeling using Hidden Markov tree and Fisher distance information is the second stage in this algorithm. The extracted features in this stage are modeled using the HMT to find the hidden information in the pattern. The models thus obtained are measured using the coefficient from the fisher distance information.

The third step of PAUCT is the validation with the known artist, whereby the extracted features are tested against the known artworks in this stage. The final output is tested and analyzed using different statistical methods to determine the accuracy of the system which is the last stage in our proposed algorithm. The Figure 1 illustrates the flowchart of the proposed PAUCT.

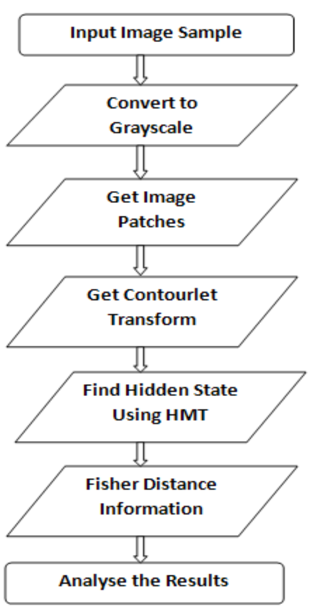


Figure 1. PAUCT flowchart.

3.1.1 Sample Collection

Selecting input is an important step in the art authentication process. As the unique signature of the artist is obtained through the feature extraction process, the proper input helps in gaining proper output. For instance, if the image is of high quality, then the best features can be extracted from the paintings, which can help with better comparison and detection of the authenticity of the paintings.

The collected input is analyzed and tested for suitability for the process of features extraction depending upon the grey intensity level of the images. Various online sources offering high resolution images are searched for the images and a reliable source is chosen for the image selection. Although Google Art Gallery seems to be the optimal source for high quality authenticated images, the image sizes they offer are very high, in gigapixels which will be extremely time consuming when processing.

Hence, the test image samples in this work have been collected from two different artists, Vincent van Gogh and Pieter Bruegel. They are grouped as the Van Gogh (VG) and Non Van Gogh (NVG) paintings as shown in Figure 2. The digital reproduction of the paintings of these two artists are distributed into two sets, Van Gog (VG) consisting of the Images from Van Gog, and Non Van Gog (NVG) which include the images from the other sources.

Figure 2. VG and NVG Data Set samples.

For the quality of collected samples, paintings that are too dark are excluded. Similarly, paintings containing only the foreground information have also been excluded. This is due to the fact that we are using background patches for our analysis. These samples have a different resolution as they are used for analysis purposes in this work to determine the authenticity of the paintings. A dataset consisting of the twenty images has been constructed. Fifteen of them were attributed to VG and five of them were attributed to NVG.

3.1.2 Feature Extraction

Feature extraction is a very important step in art authentication. The extracted features from genuine painting are modeled using the artificial intelligence algorithm and are then compared with features from the unknown paintings for the purpose of authentication. The image samples collected are in RGB format. Each image is then converted to its respective grayscale image using Matlab tool. The grayscale weighted average, y, is calculated by the formula in equation 1

$$y = 0.299R + 0.587G + 0.114bB \quad (1)$$

Those images are then divided into smaller patches, excluding the edges of the canvas. Features from these samples are extracted and cross validated against each other to determine the authenticity of the paintings. Finally, only the background patches are selected to get the respective contourelet transform of the patches. The brushstroke sample is collected and is considered as the artist's unique signature. Figures 3 and 4 show some of the samples of VG and NVG we have used and their corresponding grayscale patches.

Figure 3. Digital reproduction of the Van Gogh's paintings and the extracted background patches.

Figure 4. Digital reproduction of the Pieter Bruegel's paintings and the extracted background patches.

3.1.3 Contourlet Transform

The similarity through the appliance of the 2-D image transforms will be measured in this step. This process is supplied with the extracted image patches from the previous step. The patches are transformed using the contourlet transform that is applied to individual patches. The transform is applied and visualized using Matlab. The converted image patches undergo multi-scale decomposition.

The reasons behind choosing contourelet transform over other existing algorithms will be presented in this section. Contourelet transform is used to obtain the multi-resolution decomposition of the images. This algorithm as implementation is based on a Laplacian Pyramid. Unlike other algorithms, the number of directional high pass sub-bands can be specified by the user. These sub-bands occur at different levelsand are divided into directional sub-bands. In the [20], an image (I)can be represented in equation 2:

$$I = \sum_{i \in J} c_i \phi_i \quad (2)$$

Figure 5 shows a multi-resolution decomposition of an image at different levels. Similarly, this algorithm is designed to work on discrete data. Unlike curvelet transform which is designed to work on continuous data and which is applied to discrete data using a sampling grid. Hence with the help of contourelet transform we will be able to get a good representation of the brushstrokes in the images at different resolutions. Figure 6 shows the two level decomposition of the images using contourelet transform.

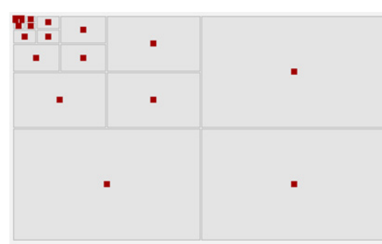


Figure 5. Multi-resolution decomposition of an image.

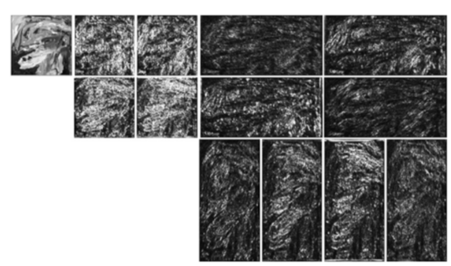


Figure 6. Level decomposition of the images using contourelet transform.

3.1.4 Hidden Markov Tree

Hidden Markov tree is a special type of the Hidden Markov Model (HMM). The extracted features are modeled in this step using HMT, to find the hidden states in the brushstrokes of the artist. The HMT and fisher distance information have been used to uncover the hidden states and measure the stylistic similarity between those object. The measured similarity is compared using the graph to determine the authenticity of the paintings (Figure 7).

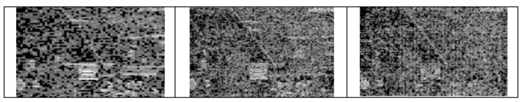


Figure 7. Extracted stylistic similarity.

For authentication purpose, the features need to be extracted from the paintings. Shape is the most important primary texture of interest. The edges of the brushstrokes patterns represent the unique signature of the artist. Contourelet transform has proven to be effective in capturing and separating edges. However, in VSUBWHFID, the features are extracted at different levels, hence it is necessary to obtain the coefficients at different scales[12]. The aim of using HMT is to capture those edges at different scales. The results are given in Table 2.

Table 2. Coefficients at different scales

Selected Biggest Coefficients		
	Initial	Kept
A8	4	4
D8	12	12
D7	48	48
D6	192	192
D5	768	768
D4	3072	3072
D3	12288	12288
D2	49152	49152
D1	196608	196608
S	262144	262144

Only few of those captured coefficients are large enough to be used as a distributional coefficient of the different sub bands. The hidden Markov tree for the contourelet transform finds different essential properties for our analysis. For a tree, A, and values {1, …., M},

The distribution of the hidden state at root,

$$P\ (Sa = m) \text{ where, } m = 1 \dots M$$

3.1.5 Fisher Distance Information

The dissimilarities between the pair of the brushwork samples has been measured. For the pair of brushwork samples, I and J, a logical measure of stylistic distance between brushwork samples i and j is the Fisher information distance between the distributions Py_i and Py_j since the true distribution is unknown. Hence, the empirical distribution of the HMT parameters Z_i and Z_j is an estimate for the true distributions Py_i and Py_j Figure 8.

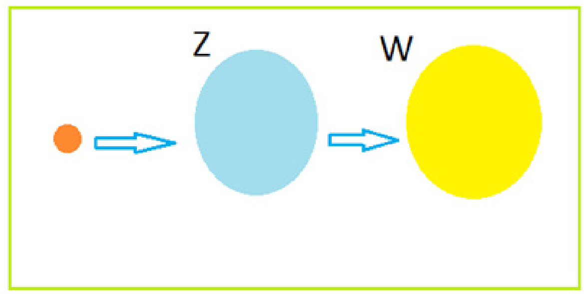


Figure 8. A generative model of style P.

3.2 PAUCT Algorithm

The proposed PAUCT algorithm described by the following steps:

Input: Test image samples (I) = $\{I_1, I_2, \dots, I_i\}$ for frame using equation 2

Output: Test image samples (I_g), Coordinates (x, y) format.

Step 0: I = 0, $I_g = 0$

Step 1: USE the Initial test image samples I as an input to the Paintings Authentication Using Contourlete Transform (PAUCT)

Function PAUCT(I)

Step 2: INPUT Test image samples I with N number of images for frame

$$I = \{I_1, I_2, \dots I_N\}$$

Step 3: START nested loop

Loop 1: FOR each Image I_i belongs to I DO

  I_g = grayscaleImage (I_i)

  EXTRACT number of patches (n) from I_g

  Loop 2: FOR each patches n DO

   IF I_g is background patch THEN

    EXTRACT contourlete transformation I_M

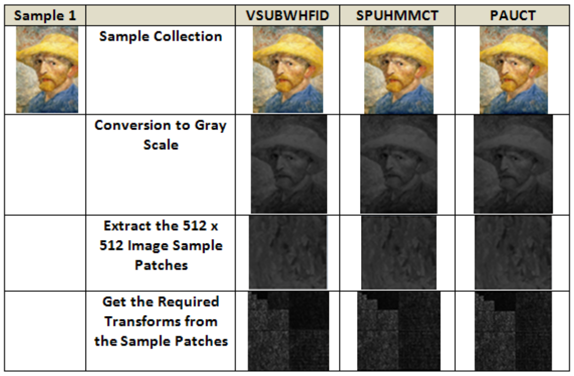
$$IM = \sum_{i \in JM} c_i \emptyset_i \tag{3}$$

where, J is the set of the M numerically larges coefficients
GET Hidden Markov Tree (HMT) parameter (HMT (T))
GET Fisher Information Distances (FD) using FINE algorithm

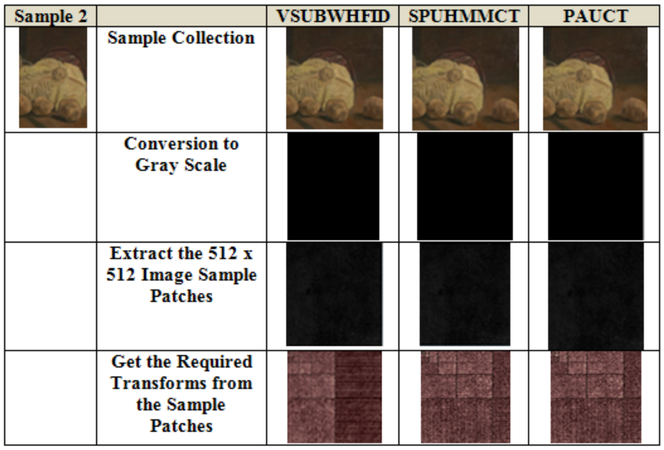
START IF CONDITION to check the distance
IF the distance is smaller THEN
Image (Ig) is authentice
RETURN image(Ig) ;
END Loop 2
END Loop 1
END

4. Rsults and Discussion

Figure 9 shows different implementation steps that compare the results of two existing algorithms; VSUBWHFID and SPUHMMCT, with the proposed PAUCT algorithms and at various steps. Wavelet HMT proposed based Fisher Information distance that has Brush Strokes extraction features and SPUHMMCT proposed HTM and Contourlet Transform that has Authenticate paintings based upon photographs from digital camera features[12, 20]. The first step shows the initially collected samples. The second step takes the sample as the input image and converts it to gray scale images. Then, the respective patch is extracted from the background of the paintings. After the patches are extracted, the respective transform is obtained as required The respective coefficients are modeled using HMT and fisher information distance is calculated as metric of stylistic similarity.



(A)



(B)

Figure 9. Samples at various stages for three algorithms.

After visualizing the obtained result, it was discovered that the proposed algorithm was able to successfully authenticate the samples with more accuracy than the other two existing solutions. Figure 10 shows the extracted coefficient values as plotted in the graph against the Van Gog (VG) and non van Gog (NVG) paintings for the purpose of measuring the similarity of the paintings. The plotted data set is analyzed and the paintings from the same artist are grouped closely.

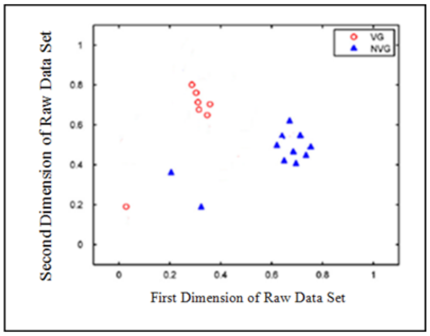


Figure 10. PAUCT results.

It also shows that the proposed PAUCT was able to successfully classify 17 out of twenty images whereas the other two current algorithms; VSUBWHFID and SPUHMMCT, were able to classify 16 and 15 out of twenty images. In PAUCT the accuracy rate is comparatively higher than the other existing algorithms. However, it can be improved with the use of proper image samples. Basically the giga pixel images can be used for the better authentication but the performance is degraded due to the algorithm capability. Figures 11 and 12 present the results of the other two algorithms that select only 15 images out of 20.

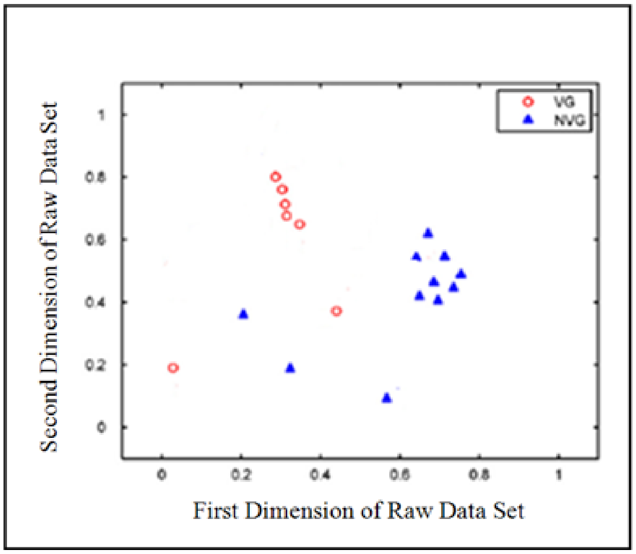


Figure 11. VSUBWHFID results.

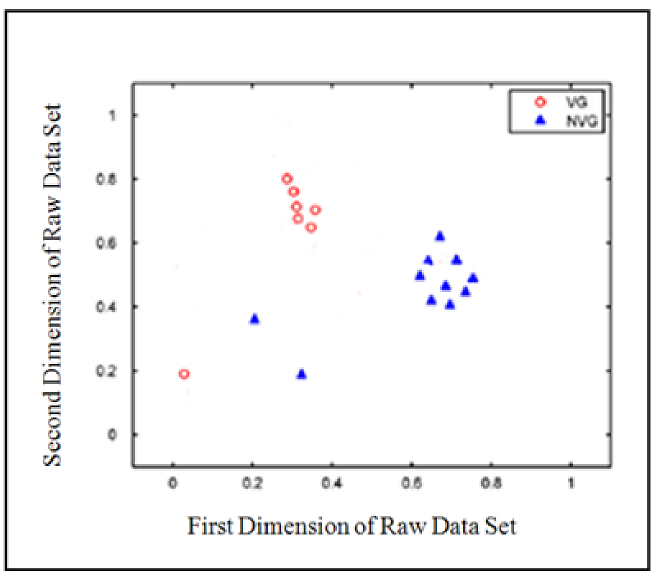


Figure 12. SPUHMMCT results.

In VSUBWHFID algorithm, the background selection process along with the use of fisher information distance has helped to gain a higher accuracy rate than the other prevalence algorithm. In the algorithm the accuracy rate is comparatively lower than the other existing algorithms. However, it can be improved with the use of proper image samples. While the accuracy in our proposed algorithm is comparatively higher than the other existing algorithms, it can be further improved with the use of proper image samples. Basically the giga pixel images can be used for better authentication but the performance is degraded due to the algorithm capability.

Although the result obtained is better than the current existing solutions, the result in itself is not at as at is factory level to be used in a real time algorithm. In order to get a better result, high resolution images are preferred to be used instead of the type of image used in this solution. I recommended using giga pixel images as they possess proper details sufficient for painting authentication. However, these images are not readily available and need large computing power for the processing. Similarly, this algorithm was only tested over twenty images from two different artists More testing and analysis is necessary to determine the efficiency of this algorithm. Likewise, this algorithm is also only tested over the genuine paintings; testing against imitated painting samples is necessary. Appendix 1 shows the comparison between all these three algorithms.

5. Conclusion

Painting authentication with the help of image processing algorithms has been a challenging task in the last decade. Different algorithms have been researched and proposed. In this work we have analyzed currently available methods and presented an algorithm of art authentication using controurelet transform. This algorithm selects the patches from the background section of the paintings and obtains the contourelet transform of those patches. The obtained transform is modeled using (HMT) to discover the hidden state. The fisher Information distance is obtained between the Hidden Markov Tree models, which is used as the stylistic distance measure between the paintings. Due to the use of these features we were able to obtain better separation of the paintings of different authors. The result shows that this algorithm has relatively higher accuracy than other current existing algorithms. However, it can be further improved with the use of proper image samples. Basically the giga pixel images can be used for better authentication but the performance is degraded due to the algorithm capability.

Table 3. Comparison of proposed PAUCT with other selected algorithms

Painting Authentication Algorithms	In[9]	In[20]	Proposed PAUCT (2015)
Work Goal	Use of wavelet based algorithm along with the HMT-Fisher distance information for the purpose of the art authentication from the background patches of the paintings.	Use of contourlet transform along with HMT regular distance information for the purpose of art authentication.	Use of contourlet transform along with the HMT-Fisher distance information for the purpose of the art authentication using the background of the paintings.
Features	The use of wavelet and HMT model along with the Fisher distance information is the main feature of this algorithm.	The use of contourlet and HMT model along with the regular distance information is the main feature of this algorithm.	The use of contourlet and HMT model along with the regular distance information is the main feature of this algorithm.
Accuracy	80%	75%	85%
Advantages	Improves the accuracy of forgery detection Improves the reliability in the digital image processing in detection of art forgery. Is more advanced in comparison to the extraction of the brushwork with the dependency on shape. Use WHMT which increases its effectiveness.	Number of directional high pass sub bands is specified by the user Is designed to work on digital images Can use the available photographs as the image data. Better than the complex wavelet algorithm	The paintings are obtained from the google art. Hence the problem of down sampling is no more. The use of contourlet transform has edge over wavelet and curve let transform which is likely to increase the accuracy of the authentication. The use of fisher information is more effective than the use of normal distance for style classification.
Limitations	Brush stroke from the dark coloured paintings cannot be extracted Cannot determine the brush strokes on the paintings foreground painting. The manual selection of background extraction point is bothersome and does not make the process fully automated.	Cannot classify images if the image is taken from different cameras. Down sampling cross camera classification is a challenge	As the features from the background paintings are selected for the feature extraction, dark paintings cannot be used. In case of the foreground paintings, where there are no background, all the image patches are analysed which is not as efficient as the background information.
Results	16 / 20 images were successfully classified. Accuracy: (80%)	15 / 20 images were successfully classified. Accuracy; 75%	17 / 20 images were successfully classified. Accuracy: 85%
Results Discussion	The background selection process along with the use of fisher information distance has helped to gain the higher accuracy rate than the other prevalence algorithm	The accuracy rate is comparatively lower than the other existing algorithms, however it can be improved with the use of proper image samples.	The accuracy rate is comparatively higher than the other existing algorithms, however it can be improved with the use of proper image samples. Basically the giga pixel images can be used for the better authentication but the performance is degraded due to the algorithm capability.

6. References

1. Lamberti F, Sanna A, Paravati G. Computer-assisted analysis of painting brushstrokes: Digital image processing for unsupervised extraction of visible features from van Gogh's works. EURASIP Journal on Image and Video Processing. 2014; 53(1):1–17. Crossref
2. Padmapriya P, Manikandan K, Jeyanthi K, Renuga V, Sivaraman J. Detection and classification of brain tumor using radial basis function. Indian Journal of Science and Technology. 2016; 9(1).
3. Cheng B, Yang J, Yan S, Fu Y, Huang T. Learning with L1-graph for Image Analysis. IEEE Transactions on Image Processing. 2010; 19(4):858–66. Crossref
4. Kumar NKS, Kumar KK, Rajkumar N, Amsavalli K. Search engine optimization by fuzzy classification and prediction. Indian Journal of Science and Technology. 2016; 9(2):1–5.
5. Condorovici R, Florea C, Vertan, C. Author identification for digitized paintings collections. IEEE International Symposium in Signals Circuits and Systems; 2013. p. 1–4. Crossref
6. Agrawal R. Design and development of data classification methodology for uncertain data. Indian Journal of Science and Technology. 2016; 9(3):1–12. Crossref
7. Qiao L, Chen S, Tan X. Sparsity preserving projections with application to face recognition. Pattern Recognition. 2011; 33(1):331–41.
8. Venkataraman S, Sivakumar S, Selvaraj R. A novel clustering based feature subset selection framework for effective data classification. Indian Journal of Science and Technology. 2016; 9(4):1–9. Crossref
9. Qi H, Taeb A, Hughes SM. Visual stylometry using background selection and wavelet-HMT-based Fisher information distances for attribution and dating of impressionist paintings. Signal Processing. 2013; 93(3):541–53. Crossref
10. Amarnath S, Balamurugan AA. Metaheuristic approach for efficient feature selection: A data classification perspective. Indian Journal of Science and Technology. 2016; 9(4):1–6. Crossref
11. Chandrappa DN, Ravishankar M, Babe RDR. Face detection in color images using skin color model algorithm based on skin color information. 3rd International Conference on Electronics Computer Technology; 2011. p. 254–8. Crossref
12. Uma KV, Appavu alias Balamurugan S. Classification of adverse event thyroid cancer using naïve entropy and association function. Indian Journal of Science and Technology. 2016; 9(4):1–7. Crossref
13. Abry P, Wendt H, Jaffard S. When van gogh meets mandelbrot: Multifractal classification of painting's texture. Signal Processing. 2013; 93(3):554–72. doi:10.1016/j.sigpro.2012.01.016. Crossref
14. Zhipeng C, Junda J, Hu H, Wenbin Z. Face detection system based on skin color model. IEEE International Conference on Networking and Digital Society; 2010. p. 664–7. Crossref
15. Khan FS, Beigpour S, Weijer J, Felsberg M. Painting-91: A large scale database for computational painting categorization. Machine Vision and Applications. 2014; 25(6):1385–97. Crossref
16. Tayal Y, Lamba R, Padhee S. Automatic face detection using color based segmentation. International Journal of Scientific and Research Publications. 2012; 2(6):1–7.
17. Saleh B, Abe K, Arora R, Elgammal A. Toward automated discovery of artistic influence. Multimedia Tools and Applications; 2014. p. 1–27.
18. Hemalatha, G, Sumathi, CP. A study of techniques for facial detection and expression classification. International Journal of Computer Science and Engineering Survey. 2014; 5(2):27–37. Crossref
19. Cetinic E, Grgic S. Automated painter recognition based on image feature extraction. 55th IEEE International Symposium in ELMAR; 2013. p. 19–22.
20. Jacobsen CR, Nielsen M. Stylometry of paintings using hidden Markov modelling of contourlet transforms. Signal Processing. 2013; 93(3):579–91. Crossref
21. Kim M, Kim J. Quantitative analysis of artists' characteristic styles through biologically-motivated image processing techniques: Uncovering a mentor to Johannes Vermeer. HCI International Posters Extended Abstracts; 2013. p. 258–62.
22. Zheng Y, Nie X, Meng Z, Feng W, Zhang K. Layered modeling and generation of Pollock's drip style. The Visual Computer. 2014; 31(5):589–600. Crossref
23. Atharifard A, Ghofrani S. Robust component-based face detection using color feature. World Congress on Engineering. 2011; 2:6–8.
24. HYang H, Lu J, Brown WP, Daubechies I, Ying L. Quantitative canvas weave analysis using 2-D synchrosqueezed transforms: Application of time-frequency analysis to art investigation. IEEE Signal Processing Magazine. 2015; 32(4):55–63. Crossref
25. Chitra S, Balakrishnan G. Comparative study for two color spaces HSCbCr and YCbCr in skin color detection. Applied Mathematical Sciences. 2012; 6(85):4229–38.
26. Manzo M, Petrosino A. Attributed relational sift-based regions graph for art painting retrieval. Image analysis and processing–ICIAP; 2013. p. 833–42. Crossref

27. Jankowski M. Erosion, dilation and related operators; 2006. p. 1–6.
28. Liu H, Chan RH, Yao Y. Geometric tight frame based stylometry for art authentication of van Gogh paintings. arXiv preprint; 2014.
29. Hughes JM, Mao D, Rockmore DN, Wang Y, Wu Q. Empirical mode decomposition analysis for visual stylometry. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2012; 34(11):2147–57. Crossref
30. Wu T, Polatkan G, Steel D, Brown W, Daubechies I, Calderbank R. Painting analysis using wavelets and probabilistic topic models.20th IEEE International Conference on Image Processing; 2013. p. 3264–8. Crossref
31. Ramalingam V, Balasubramanian C, Palanivel S. Tumor diagnosis in MRI brain image using ACM segmentation and ANN-LM classification techniques. Indian Journal of Science and Technology. 2016; 9(1):1–12.