Model Based Approach for Identification of Relevant Images from Ancient Paintings

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Abstract

In this paper an attempt is made to retrieve the relevant paintings based on the approach of the artist using Generalized Bivariate Laplacian Mixture Model (GBLMM). This article helps in understanding the outline of assorted artists and help as a means to categorize a scrupulous painting based on the style or the text ingrained within the images. To profile the artist style GBLMM is used. The projected model helps to discriminate the strokes of the artists and lend a hand in the classification of paintings. The proposed model is implemented using high resolution Chinese painting images.

Index Terms: GBLMM, classification, painting, retrieval, stroke.

1. Introduction

The area of image processing helps in better understanding the inherent details within the images. With the evolution of technologies, efforts are initiated to digitize the ancient arts and paintings [1]. Every artist holds his individual means of narration and depicts the same in the form of paintings. One can analyze the paintings that are digitized using the internet facility. Accordingly different algorithms have been developed to analyze the ancient digitized paintings [2]. Meaningful deductions can be made from the available literature, in better understanding the narrative styles of the artists. However, each painting has its own features, and each artist has his own way of drawing patterns, thereby the strokes applied among the artists differ. Several researchers have proposed methodologies to identify and classify the paintings based on features, digital signatures, frequency of application of a particular stroke etc. [3],[4],[5].

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Among these models, models based on parametric and non-parametric are focused. However, most of the presented works are totally based on the classification, and identifying the relevancy based on particular metrics [3]. Moreover, while classifying the images based on features, the variation among the pixels is not taken into account. Very little importance is highlighted towards the loss of connectivity among the pixels. Therefore effective classification of the relevant images based on either artistic styles or based on specific artist cannot be categorized effectively. In this proposed article an attempt is made to bridge these gaps in this direction.

To every image, a Meta tag is associated and each the images along with the tags are modelled using GBLMM. The classification process is carried out using the maximum likelihood estimate. The rest of the paper is organized as follows. In section II of the paper, the related work is presented. The section III highlights the major challenges with respect to the retrieval of relevant images. Section IV of the paper presents the GBLMM model along with the methodology. Section V highlights the feature extraction and the dataset considered together with experimentation is highlighted in section VI of the paper. The results derived together with evolution are highlighted in section VII and the final section VIII concludes the paper.

2. Related Work

Many authors have highlighted the methodologies for effective identification of the artistic images from the ancient paintings. C.C.Chen et al. (2002), have presented an idea of the ancient document together with the databases. Bouman, Liu (1991), have utilized the Markov model for segmenting the images. Choi and Baraniuk (1999), considered the hidden Markovian models for segmenting the images. The concept of gray scale document segmentation is utilized by Chaddha et al. (1994). The concept of thresh holding, VQ models, Bayes classification, segmentation of half toning are proposed by A.P.Dhawan et al. (1996), Sherbini (1995), Groes et al. (1995), Loum G et al. (1996), Mallet S.G (1989), F.Y.Shih (1996). In the article presented by Razvan George Condorovici et al (2013), the authors presented a model for automatic system that recognises Artistic genre identification. This is an integral part of the effective image processing systems aimed towards better understanding of artistic view. A relevance feedback mechanism was highlighted by Bogdan Boteanu et al (2014) in which the authors tried to retrieve the relevance images based on the query, it integrated the approaches of automation power of machines together support vector machine and relevance feedback mechanisms. Parag Dhonde et al (2015) have presented a model of image mining using the concepts of hierarchical K-Means algorithm and image vision tools to retrieve the images of interest. The concepts of parametric modelling were considered for classification of images and an elaborate study was presented by the authors Srinivas.Y (2007), Nagesh V (2010), Madhusudhan T (2013) and Anuradha P (2014).

3. Major Challenges

In spite of extensive works in this area, effective segmentation and classification is still a concern. This is due to fact that the features are extracted locally basing on which the segmentation is carried out, which results into core technical problems in case of similar images. The second challenge is with respect to the breaks in the images, in some of the images the variation among the inks cannot be identified exactly because of a low changes in the colour tones. Strokes of the artist also play vital role and very little attention is paid to identify the exactness of the strokes. To overcome this challenges, in this paper we have considered the GBLMM.

4. Generalized Bivariate Laplacian Mixture Model

The Probability Density Function (PDF) of GBLMM is given as

$$f(x,y) = \frac{1}{\pi \sigma_1 \sigma_2 \sqrt{(1-\rho^2)}} . k_0 . \sqrt{(2(x^2/\sigma_1{}^2 - 2pxy)/(\sigma_1 \sigma_2) + \frac{y^2}{\sigma_2{}^2})/(1-\rho^2))} \qquad (1)$$

Where

k_0 is the Bessel function, ρ is scale parameter, $0 \leq \rho \leq 1$ (2)

The main consideration of GBLMM is that its ability to identify the variation among the regions with in the images. The image is divided into parts using discrete wavelet Harr transformation and the different regions LL, LH, HL, and HH are identified. The LL band helps to identify the low variations inside the images, variations along the horizontal direction can be attributed using HL bands, LH bands are considered for changes along the vertical direction and HH are utilized for identifying the high intensity image regions.

Each image is considered and the histograms are extracted using which the various bands such as LL, LH, HL and HH are identified. Each of the pixels within these bands is identified and is modelled using the GBLMM and the relevant PDF are identified. In order to minimize the space complexity, each of these bands are further subdivided and the highest frequency values are considered from each of these such bands and these values are given as inputs to the PDF of GBLMM given in section 3 of the paper. This is called the training phase. In the testing phase, the relevant images are extracted by comparing the similarity among the PDFs for which KL-divergence is considered. The derived images are subjected to quality metrics for identification of the similarities.

5. Feature Extraction

To extract the features the images divided into sub bands containing LL, LH, HL, and HH features. Each of these sub bands are further sub divided and a unique feature vector is identified from each of these sub bands. These unique vectors are given as input for modelling the images using GBLMM proposed section 3 of the paper.

6. Dataset Considered

In ordered to proposed methodology we have considered the ancient paintings of the Chinese artists from the internet and in particular we have considered the paintings of Van Gogh, Zhang daqian given in the report of C.C.Cheng et al. (1996).

Fig.1. Dataset Considered

6.1. Meta Tags

Every image considered is associated with a Meta tag. These Meta tags are given as another feature for the GBLMM as input. The various tags considered are presented in the following Table 1.

Table 1. Image with the Tags

File Name	TAG
1ce1135a4a26ea08847bc18d7e4ef81e.jpg	ancient, Chinese, singing, song, red, horse cart, moon
4a1bc7599efb16e29d4e8cea94afbcaf.jpg	ancient, Chinese, king, palace
Ancient-Chinese-gods-2.jpg	ancient, Chinese, women, a tinge, vermeil, sweet hearted ancient, Chinese, committee
ancient-chinese-architecture-08.jpg	ancient ancient, Chinese, tang game
ancient_chinese_women_e7df5562.jpg	ancient, Chinese, xianterra, cota,warriors
Ancient-Chinese-Social-Ranks.jpg	song,yingxing,chinese,scientist,encyclopedist and ,tiangong kaiwu,an encyclopedia
doctor.jpg	mohism,ancient,chinese,philosophy
committee.jpg	ancient, Chinese, architecture, temple
group3.jpg	ancient, Chinese, doctor
images.jpg	ancient, Chinese, soldier
making_of_jonathan_spence.jpg	ancient, Chinese, priest, education, scholarship
mohism__ancient_chinese_philosophy.jpg	Ancient, Chinese, god
song_yingxing_a_chinese_scientist.jpg	Ancient, Chinese, Social, Ranks
xianterracotawarriors.jpg	ancient, Chinese, jonathan,spence,scholar
123px-Riza- Abbasi_008.jpg	Saki, Reza Abbasi, Moraqqa e, Golshan, Golestan Palace, ancient, Chinese
220px-Saki_-_Reza_AbbasiPalace.jpg	Riza, yi, Abbasi, ancient, Chinese
220px-Mir_Sayyid_Ali_2.jpg	Behzad, advice, ascetic, ancient, Chinese
300px-Behzad_advice_ascetic.jpg	ancient, Chinese, Mir Sayyid Ali story
220px-Jami_al-Tawarikh_Miraj.jpg	ancient, Chinese, Jami al Tawarikh Miraj

7. Results

In order to present the methodology, we have considered the dataset as discussed in section 6, the dataset consists of the paintings of ancient Chinese artists. Along with these paintings a narration about the paintings or the name of the artist is also included. In our methodology we have considered these descriptions as the tags and retrieval is carried out using these tags as a feature. Each image with the tag as index is given as input to the model and the corresponding Probability Density Functions (PDFs) generated against each of these images are noted in a matrix. In general there is a possibility of repetition of tags and therefore the retrieval efficiency degrades in most of the cases. In order to overcome this challenge, in the present model we have considered more than one tag as the index. The images that are retrieved against each of these tags is presented in the following Fig 2.

Fig.2. Retrieved images, based on Tags

The above methodology is tested against quality metrics such as Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) The formulas for calculation of each these metrics is presented in the paper authored by Srinivas Y et al (2010), Nagesh V et al (2011), Madhusudhan et al (2013). Using the above heuristics, the results derived are presented in Table 2.

From the above table it can be clearly seen that the MSE of the retrieved image against the query image is nearing to zero. This implies that the retrieved image is very much nearer to the query image. The PSNR values highlight the same. From the values presented in the Table 2, it can be seen that the developed model helps in better retrieval of the images.

Table 2. Performance Evaluation

Image	MSE	PSNR
	0.7	32.80
	0.87	36.70
	0.79	38.00
	0.89	41.00
	0.90	44.30
	0.85	40.20
	0.76	38.20
	0.88	40.76
	0.85	40.10
	0.82	40.01
	0.876	40.10

8. Conclusions

This paper highlights the methodology for the retrieval of ancient images based on the features which we have considered to be the tags. The proposed methodology helps for the better retrieval against the existing methods. This methodology is very much suited for the archaeologists for identifying the ancient paintings of a particular artist.

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