Mobile-Based Painting Photo Retrieval Using Combined Features

Claudia Companioni-Brito[1], Zygred Mariano-Calibjo[1], Mohamed Elawady[2(✉)], and Sule Yildirim[1]

[1] NTNU - Norwegian University of Science and Technology, Gjøvik, Norway
sule.yildirim@ntnu.no

[2] Université de Lyon, UJM-Saint-Etienne, CNRS, IOGS, Laboratoire Hubert Curien UMR5516, 42023 Saint-Etienne, France
mohamed.elawady@univ-st-etienne.fr

Abstract. In paintings or artworks, sharing a photo of a painting using mobile phone is simple and fast. However, searching for information about specific captured photo of an unknown painting takes time and is not easy. No previous developments were introduced in the content-based indexing and retrieval (CBIR) field to ease the inconvenience of knowing the name and other information about an unknown painting through capturing photos by mobile phones. This work introduces an image retrieval framework on art paintings using shape, texture and color properties. With existing state-of-the-art developments, the proposed framework focuses on utilizing a feature combination of: generic Fourier descriptors (GFD), local binary patterns (LBP), Gray-level co-occurrence matrix (GLCM), and HSV histograms. After that, Locality Sensitive Hashing (LSH) method is used for image indexing and retrieval of paintings. The results are validated over a public database of seven different categories.

Keywords: CBIR · Image features · Similarity · Indexing · Paintings

1 Introduction

Analysis of artworks using computer vision is an interesting cross-disciplinary field that is being utilized in different industries such as architecture, advertising, design, fashion and art conservation [1,2]. Through CBIR, retrieval of similar image in the database to that of a query image through comparison of the extracted features of the images is possible [3–5]. This work focuses on art image retrieval framework respect to the museum paintings, through understanding the aesthetic and technical content of artworks. Painting photo retrieval is introduced in this paper using combined visual features based on shape, texture and color information. These features are well-detected in both global and local scale, for the purpose of efficient feature comparisons [2,4,6]. In the end, the top paintings similar to the input painting photo will be displayed together with the

A. Campilho et al. (Eds.): ICIAR 2018, LNCS 10882, pp. 278–284, 2018.
https://doi.org/10.1007/978-3-319-93000-8_32

information about each of them. Hence, instant access to painting information about an unknown painting will become possible through mobile applications inside nowadays smart phones. The proposed framework is validated using a large-scale database of digitized painting images. The contributions of this work are (1) feature extraction using shape features in CBIR systems, and (2) combined feature representation for art paintings indexing and retrieval. The paper is organized as follows. Section 2 introduces a fully-automated image indexing and retrieval framework. In Sect. 3, the experimental results of the proposed work on paintings are shown and discussed. Finally, summary and future work were concluded in Sect. 4.

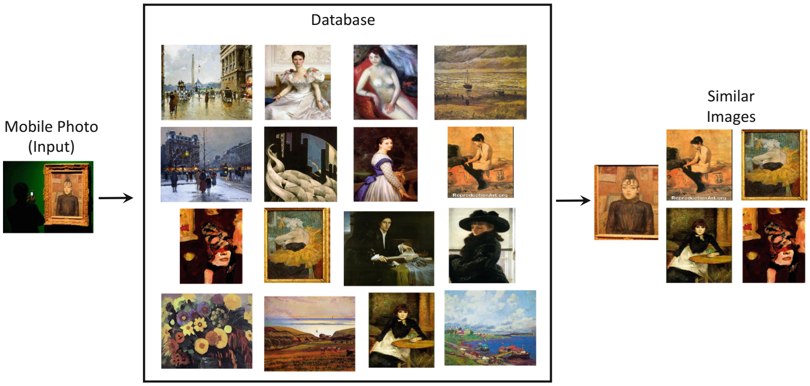

Fig. 1. Illustration of a query scheme within the corresponding retrieval results.

2 Methodology

In this work, we propose a general image retrieval system based on a combined feature representation between color, texture and shape features. As shown in Fig. 1, the proposed retrieval framework will start with an input image (i.e. real-time mobile photo). This image is known as a query image. Regardless of the resolution of the query image in RGB, it will be resized for computational efficiency and then converted to HSV color space. The dominant color of the image will be extracted as color feature vectors through a clustering-analyzing algorithm and using HSV histogram [6]. To extract the texture features, capacity, entropy and relevance of an image are calculated by the gray level co-occurrence matrix (GLCM) and local binary pattern (LBP) algorithms [7]. After extraction of texture features, shape descriptors will be used to extract the outline of the objects present in the image. As shown in Fig. 3, image signature saliency, Otsu binary thresholding and generic Fourier descriptors algorithms will be utilized because they are robust to noise and have translation, rotation and scale invariance [8–11]. After the feature extraction of a query image, these features will be matched with the same extracted ones of all images in the painting database.

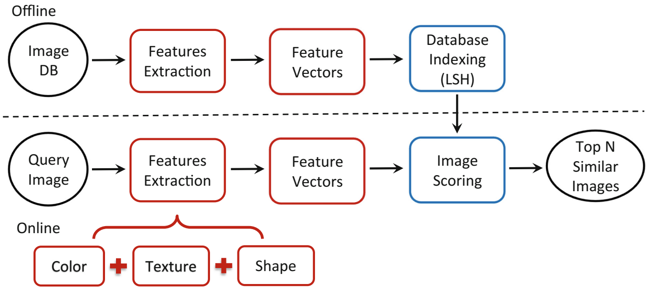

Fig. 2. The proposed framework of content-based image retrieval.

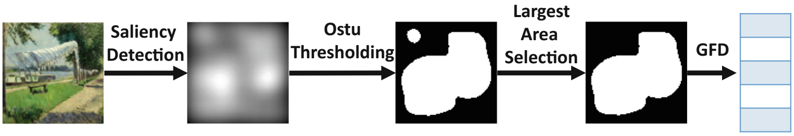

Fig. 3. Steps of shape feature extraction.

Comparison and matching of a query image with the database images will be based on low-level features previously discussed. Ranking of top similar images will be implemented by calculating $l1$ norm distance (direct comparison) between the feature vectors of the query and the database. These similar images will be ranked according to the distance from smallest to largest [6]. For the sake of computation time, similar images can be also ranked using an effective indexing algorithm called Locality Sensitive Hashing (LSH) [12]. The output of the proposed algorithm will be the top similar painting images from the large-scale database.

3 Results and Discussion

In order to evaluate the effectiveness of the proposed framework, it was applied on Kaggle Painting Database through pre-selecting 5,150 digital images representing paintings from different artists. The size of each category is as follows: abstract (993), cityscape (948), flower (334), landscape (994), marina (414), nude (513), and portrait (954). The proposed work is implemented using MATLAB (R2016b) on a Windows-based PC platform. The database images are experimentally down-sampled into 100×100 for fast computation without effecting the system performance. Figure 4 shows some sample images of selected categories. For HSV histograms, the number of quantization levels are 8:2:2 for Hue, Saturation, and Value channels respectively. The output representation of GLCM features is as follows: energy, contrast, correlation, homogeneity and entropy. The cell size for LBP feature extraction set to 3×3. The angular and radial frequencies of generic Fourier descriptors set to 12 and 5. For LSH indexing

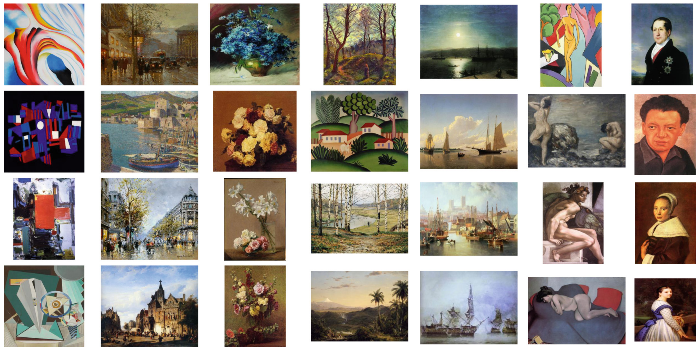

Fig. 4. Sample images from seven categories of Kaggle database in column-wise.

method, the number of hashing tables is 3, and the length of keys is 6. The output dimensions of color, texture and shape features are: HSV (32), GLCM (5), LBP (36), and GFD (78). Afterwards, these features are normalized using $l2$ norm. The combined feature representation can be constructed by concatenating the proposed feature vectors.

Fig. 5. Retrieval results of top 5 similar images for the Cityscape (1st row) and Portrait (2nd row) categories using: (a, c) LSH indexing and (b, d) direct comparison.

The performance of the proposed CBIR framework is presented in Fig. 5, and measured using precision-recall and ROC curves in Fig. 6. Plus statistical results present in Table 1. We compare the proposed ranking methods (LSH,

Table 1. Results of retrieval framework using LSH and Direct comparison for all queries. Time is in seconds.

	LSH			Direct comparison		
Query	Time	Recall	Precision	Time	Recall	Precision
Abstract	0.07	0.002	0.4	0.08	0.001	0.2
Cityscape	0.06	0.003	0.6	0.08	0.002	0.4
Flower	0.08	0.006	0.4	0.07	0.003	0.2
Landscape	0.06	0.005	1.0	0.08	0.005	1.0
Marina	0.06	0.007	0.6	0.08	0.004	0.4
Nude	0.07	0.008	0.8	0.07	0.008	0.8
Portrait	0.06	0.004	0.8	0.07	0.004	0.8

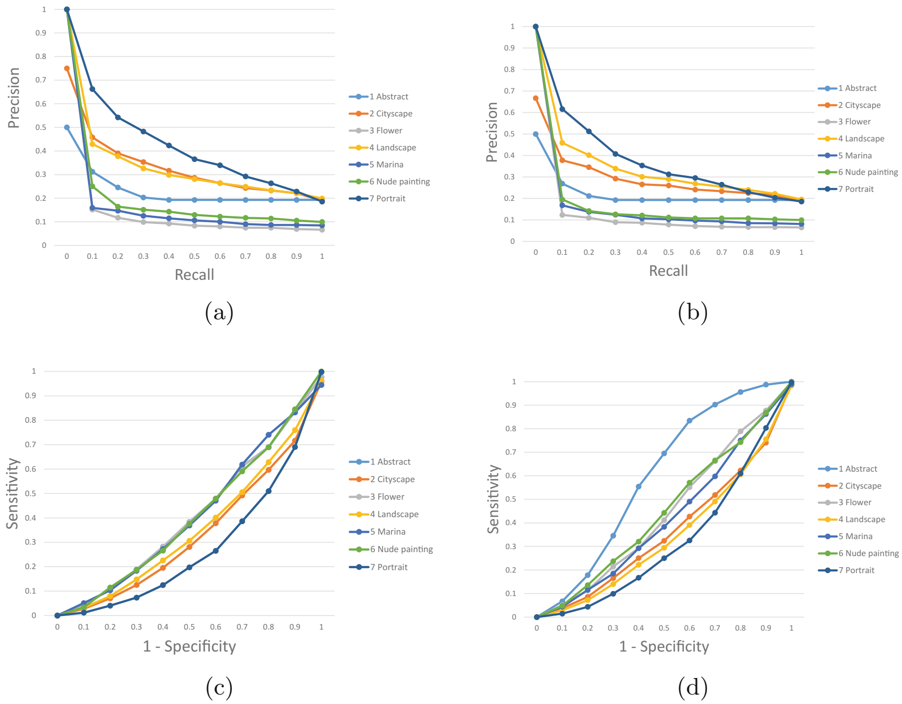

Fig. 6. Performance results of using (a, c) LSH indexing against (b, d) direct comparison. Columns represent precision and recall and ROC curves respectively.

direct comparison) to confirm the significance of indexing in reducing retrieve time. Figure 5 shows the result of two systems, with and without indexing, for a query on cityscape. Color indeed plays a significant role in image retrieval as shown by the top 5 similar images. Shapes also played a significant role, but not as dominant as color. Texture has the least effect in retrieval of similar images, with or without indexing. In the first example, cityscape was the query image and the results displayed images from marina and landscape. This kind of result will greatly affect the precision and recall of the image as well as the user satisfaction. This issue can be a topic for next researches to better understand how certain feature vectors affect the retrieval of images. In Fig. 6. Flower query has the lowest precision while portrait has the highest. As shown in Table 1, indexing indeed makes the system of retrieval faster. Though the result of recall and precision did not significantly change, as shown in Fig. 6. Having faster retrieve time will make any system efficient and effective. Hence, LSH indexing is deemed significant to the proposed framework more efficient and effective.

4 Conclusion

The proposed image retrieval framework for painting images is a significant contribution to CBIR as well as to the industries dealing with painting photographs. The qualitative and quantitative experiments showed good results using the combined feature representation, to retrieve similar painting images respect to the captured photo. This work significantly helps museums or any art institution to deliver better experience to their audience. In the future work, the shape feature extraction can be improved by segmenting the salient objects precisely from the scene background. In addition, the combined representation can be also included the deep features from pre-trained CNN models for better accuracy.

References

1. Khan, F.S., Beigpour, S., Van de Weijer, J., Felsberg, M.: Painting-91: a large scale database for computational painting categorization. Mach. Vis. Appl. **25**(6), 1385–1397 (2014)
2. Soman, S., Ghorpade, M., Sonone, V., Chavan, S.: Content based image retrieval using advanced color and texture features. In: International Conference in Computational Intelligence (ICCIA), vol. 3 (2012)
3. Kavitha, K., Sudhamani, M.: Object based image retrieval from database using combined features. In: 2014 Fifth International Conference on Signal and Image Processing (ICSIP), pp. 161–165. IEEE (2014)
4. Wang, X.Y., Chen, Z.F., Yun, J.J.: An effective method for color image retrieval based on texture. Comput. Stand. Interfaces **34**(1), 31–35 (2012)
5. Zhou, W., Li, H., Tian, Q.: Recent advance in content-based image retrieval: a literature survey. arXiv preprint arXiv:1706.06064 (2017)
6. Yue, J., Li, Z., Liu, L., Fu, Z.: Content-based image retrieval using color and texture fused features. Math. Comput. Model. **54**(3), 1121–1127 (2011)
7. Bianconi, F., Harvey, R., Southam, P., Fernández, A.: Theoretical and experimental comparison of different approaches for color texture classification. J. Electr. Imaging **20**(4), 043006–043006 (2011)
8. Amanatiadis, A., Kaburlasos, V., Gasteratos, A., Papadakis, S.: Evaluation of shape descriptors for shape-based image retrieval. IET Image Process. **5**(5), 493–499 (2011)

9. Zhang, D., Lu, G.: Content-based shape retrieval using different shape descriptors: a comparative study. In: null, p. 289. IEEE (2001)
10. Hou, X., Harel, J., Koch, C.: Image signature: highlighting sparse salient regions. IEEE Trans. Pattern Anal. Mach. Intell. **34**(1), 194–201 (2012)
11. Zhang, D., Lu, G.: Shape-based image retrieval using generic fourier descriptor. Sig. Process. Image Commun. **17**(10), 825–848 (2002)
12. Datar, M., Immorlica, N., Indyk, P., Mirrokni, V.S.: Locality-sensitive hashing scheme based on p-stable distributions. In: Proceedings of the Twentieth Annual Symposium on Computational Geometry, pp. 253–262. ACM (2004)