Light Field Retrieval In Compressed Domain

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ABSTRACT

In this paper, we present a novel approach for light field retrieval in the transformed domain. The light field data set is characterized with low wavelet transform coefficients. Our algorithm first applies a wavelet transform on 20 key images of the light field structure. The low wavelet transform coefficients are then quadtree decomposed, into a set of homogeneous blocks. Each set of homogeneous blocks represent an object in the considered image. We use texture and color features to characterize the object image; the similarity between two images is measured by matching their histograms. The experimental results and comparisons show the performance of the proposed technique.

Keywords

light field, retrieval, similarity measures, wavelet analysis, quadtree.

1. INTRODUCTION

The rapid advance of digital technologies has improved the methods of acquisition and rendering of 3D models. We can see today that the databases of 3D objects are present in many areas: games, multimedia, medical applications, cultural heritage.

The ease of acquisition and reconstruction of 3D models allows large databases creation, so it becomes difficult to navigate and find information. Indexing 3D objects thus appears as a necessary and promising solution to manage this new data type.

Current 3D models search engines use 2D shapes drawn by user as a query image. The objective is to find relevant 3D models efficiently and correctly by querying from a database models. In other words, we search the most similar model of the database to the query [1]. The proposed approach in [2] is based on 20 silhouettes characterization. This method represents the object in 20 different locations on the sphere. The 20 views are used to construct a combined texture and color feature, which characterizes the captured 3D object. Chen et al. [1] propose to match 3D objects based on view similarity measure. Other view based retrieval methods use 3D models matching according to geometric distribution, topology structure and curvature of a patch [3].

These approaches achieve good retrieval scores, however higher dimension points make the analysis more difficult. Image-based retrieval methods try to address this problem by measure the similarity between rendered projections. Ohbuchi et al., for instance, propose a characterizing scheme of each view image using the SIFT algorithm [4]. Local features were then integrated into a histogram using a bag of features approach for retrieval.

Light field is a structure-based image representation for interactive visualization of any new point of view leading to high data volume. To reduce the cost of storage of light fields, one can combine the two operations of transformation and indexing to achieve retrieval directly in the transformed domain.

In this paper, we propose a light-field-based image retrieval in the wavelet domain. This system uses an approximated light field representation as proposed in [2], which considers only 20 captured key views from a fixed set of positions on the sphere. Each view object is firstly converted into YC_bC_r space and then each image component Y, C_b, C_r is transformed using wavelet. The resulting low frequency coefficients are decomposed into homogeneous blocks by quadtree. We finally construct texture and color features from the low-pass band of the wavelet transform. These features are organized into a histogram to describe the object. At the end, the retrieval step is based on the similarity measure using Euclidean distance between the query view and candidate views.

The rest of this paper is organized as follows. We first describe the acquisition system [4]. Next we describe our method for conversing and transforming light fields. We then explain the texture and color features construction. Finally, we present and analyze the results from our experiments and provide a conclusion.

2. Data acquisition system

The acquisition system (Figure 1) used in [5] takes in consideration all rotations, scaling and moving of the object.

Ameshin [5] proved that this acquisition system of light fields offers the best possible correlation alignment between the models. So our indexing system, to be efficient, must be robust to rotation, displacement and scale change.

In our case, we use an image data base [7] acquired in accordance with the system described above.

We then select only 20 views with 18° rotation angle between two consecutive cameras. Obtained views represent the light field of the object.

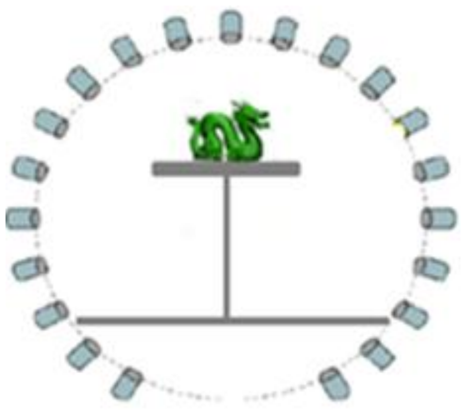

Figure 1. Acquisition system

3. The proposed scheme

The proposed approach consists of two steps: firstly, we use wavelet transformation and secondly, we apply quadtree segmentation onto the low frequency coefficients.

3.1. Wavelet transformation

First, color image is converted from RGB to YCbCr and the image components (Y, Cb, Cr) are transformed using wavelet decomposition based on the biorthogonal Cohen–Daubechies–Feauveau 9/7 (CDF 7/9) filters.

Each component is decomposed up to 2 levels.As shown in Figure 2, each image is converted into 3 components YCbCr.

For each image component transformed using DWT CDF 9/7, we consider only low wavelet coefficients, for image characterization with texture and grey level histograms.

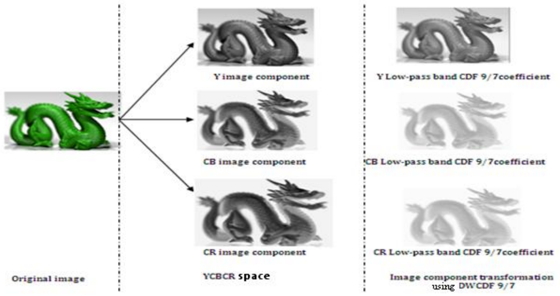

Figure 2. View transformation using CDF 9/7 wavelet transform

3.2. Image quadtree decomposition

Each low frequency sub-band is successively decomposed into quadrant depending on the complexity of the coefficients. The sub images are then iteratively decomposed until all blocks are homogenous (figure 3): the standard deviation of the coefficients within the block is below a predefined threshold. A sub image is considered to be homogeneous block if its standard deviation is lower than the threshold.

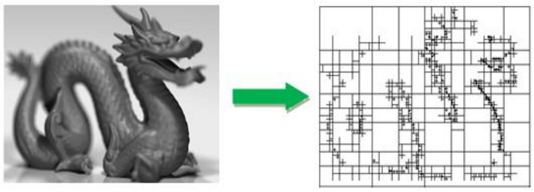

Figure 3. Image quadtree decomposition

4. Light field view indexing

Based on the quadtree-decomposed sub-bands, texture features and color features are extracted.

4.1. Texture feature construction

Firstly, for each image block of each component, the co-occurrence matrix is constructed. This matrix characterizes the texture of each image block by calculating how often pairs of pixels, with specific values and in a specified spatial relationship, occur in a block [9]. From this matrix, we calculate the following statistical measures (figure 4) to be texture features:

Energy feature: is the squared sum of the values of the co-occurrence matrix.

$$\sum_{i,j} P(i,j)^2 \qquad (1)$$

Contrast feature: represents the contrast distance between two matrix elements.

$$\sum_{i,j} |i-j|^2 P(i,j) \qquad (2)$$

Homogeneity feature: measures the distribution of the co-occurrence matrix elements around the diagonal.

$$\sum_{i,j} \frac{P(i,j)}{1+|i-j|} \qquad (3)$$

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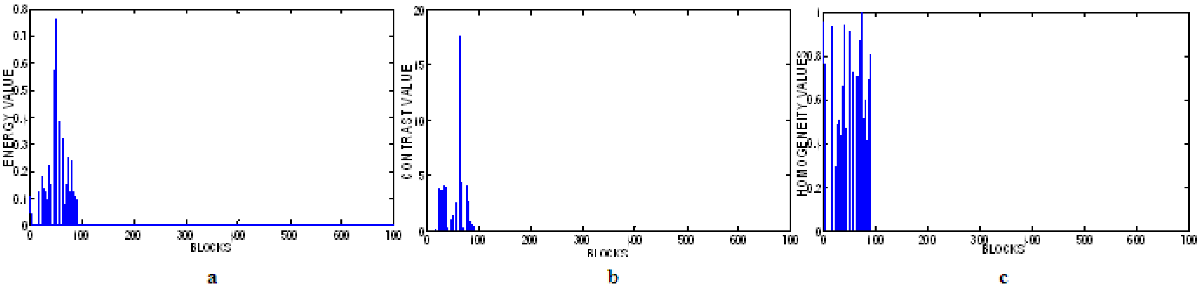

Figure 4: examples of texture image features: (a) energy feature, (b) contrast feature, (c) homogeneity feature.

Now, each image block is characterized by the mean values of its energy, contrast and homogeneity from the corresponding blocks in the three components (Y, C_b, C_r):

$$Energy=(Y\_E+C_b\_E+C_r\_E)/3 \quad (4)$$

$$Contrast=(Y\_C+C_b\_C+C_r\_C)/3 \quad (5)$$

$$Homogeneity=(Y\_H+C_b\_H+ C_r\_H)/3 \quad (6)$$

where x_E, x_C and x_H are the Energy, the Contrast and the Homogeneity values respectively from the x component. Figure 4 shows an example of these textures parameters.

4.2. Color feature construction

The second step of our indexing consists of color vectors construction using the mean value of each block of the image components.

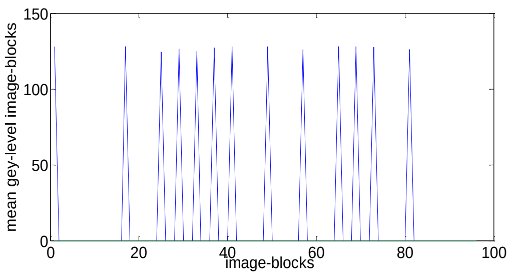

Figure 5. Example of color feature

Figure 5 represents the color image feature, which is the mean of grey level values in the domain Y, C_b, C_r respectively:

$$Color = (Y\_gl + C_b\_gl + C_r\_gl)/3 \quad (7).$$

where Y_gl, C_b_gl and C_r_gl are the gray-level values of the image blocks in the respective components Y, C_b and C_r.

Once all the features have been extracted, every homogeneous block is represented by a four-element vector as <Gray_level, Energy, Contrast, and Homogeneity> (Figure 6).

4.3. Histogram generation

The histogram of the Energy feature represents the frequencies of all the texture energy values. This histogram is then quantized into M bins such that:

$$H\_E= \{h (b_1) , h (b_2) \; \ldots h (b_M) \} \quad (8)$$

With M=32 bins and where $h(b_i)$ is the frequency of the texture energy value at bin b_i.

The same method is used to construct the contrast, homogeneity and color histograms H_C, H_Ho, and H_Cl, respectively. Figure 6 clearly illustrates that there is a few histogram values that appear in high frequency in the histograms. This figure shows that the first bins are the dominant ones in the histogram [8]. To reduce the length of the histogram features, only high frequency 32 first bins are selected to form a reduced histogram. As stated in [8], such representations can yield better image characterizing.

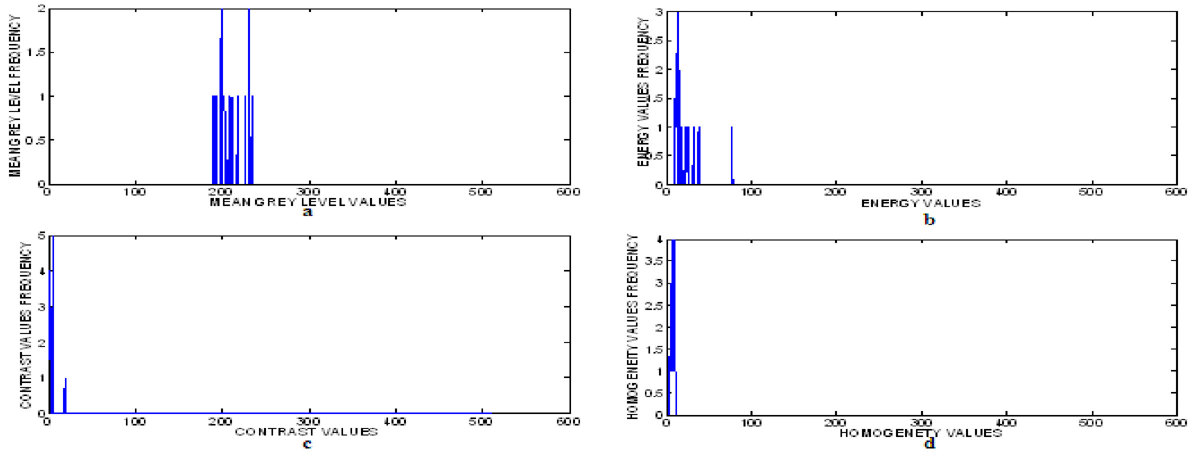

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Figure 6. Color (a), Energy(b), contrast(c) and homogeneity(d) histograms

4.4. Similarity Measurements

As many of current Retrieval approaches, our similarity measurement is based on the Euclidian distance of the histograms:

$$D = \sqrt{\sum_{i=1}^{n}(HCi - HQi)}^2 \qquad (9)$$

Where H_C and H_Q are the feature histograms of candidate image C and Query image Q respectively with size n.

5. Experimental Results

The proposed algorithm is tested on a database of images. The database consists of 100 images having 5 image categories with 20 vies each. All images are in the RGB space. In order to measure retrieval effectiveness for our image retrieval system, we use the precision and recall values. We select three different images of each category as query images.

The resulting Euclidian distances between the query image feature histogram and each feature histogram in the database, are used to evaluate our retrieval system.

$$\text{Precision}=\frac{\text{number of relevant images retrieved}}{\text{total of images retrieved}} \qquad (10)$$

$$\text{Recall}=\frac{\text{number of relevant images retrieved}}{\text{total number of relevant images in database}} \qquad (11)$$

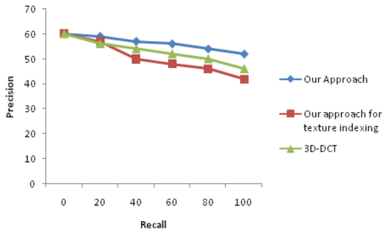

Figure 9. Our retrieval method evaluation

A number of experiments were performed to evaluate the performance of our proposed approach and its variants. The upper graphs show the retrieved results using our approach and testing our approach with texture database respectively. The retrieved results are ranked in the top ten in similarity. It can be found that our method would perform better than the 3D-DCT method in terms of the precision rate.

6. CONCLUSION

In this work we have addressed the problem of light field access by the constitution of an indexing system and image retrieval in the transformed domain. The proposed solutions were evaluated in the context of image based light field retrieval. These solutions allow to reduce the comutational complexity and the discriptions length.

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REFERENCES

[1] Yu-TeShen, Ding-Yun Chen, Xiao-Pei Tian and Ming Ouhyoung 3D Model Search Engine Based on Lightfield Descriptors EUROGRAPHICS 2003 / J. Flores and P. Cano

[2] Y.-T. Shen D.-Y.Chen, X.-P.Tian and M. Ouhyoung. On visual similarity based 3D model retrieval. In Eurographics, 2003.

[3] L. Cieplinski, M. Kim, J.-R. Ohm, M. Pickering and A. Yamada, "Text of ISO/IEC 15938- 3/FCD Information Technology - Multimedia Content Description Interface - Part 3 Visual", ISO/IEC JTC1/SC29/WG11/N4062, Singapore, Mar. 2001.

[4] R. Ohbuchi, K. Osada, T. Furuya, and T. Banno. Salient local visual features for shape-based 3D model retrieval. In Shape Modeling International, 2008.

[5] Ameesh Makadia and Kostas Daniilidis, Light Field Similarity for Model Retrieval EUROGRAPHICS 2003 / P. Brunet and D. Fellner

[6] Shou-Yi Tseng, Zhi-Yu Yang, Wen-Hsuan Huang, Chin-Yi Liu and Yi-Huei Lin Object Feature Extraction for Image Retrieval Based on Quadtree Segmented Blocks 2009 World Congress on Computer Science and Information Engineering.

[7] http://web.media.mit.edu/~gordonw/SyntheticLightFields/

[8] Chuo-Ling Chang, Xiaoqing Zhu, Prashant Ramanathan, and Bernd Girod, Light Field Compression Using Disparity-Compensated Lifting and Shape Adaptation IEEE transactions on image processing, vol. 15, no. 4, april 2006.

[9] Haralick, R.M., and L.G. Shapiro. Computer and Robot Vision: Vol. 1, Addison-Wesley, 1992, p. 459

[10] Cong BAI, Kidiyo KPALMA and Joseph RONSIN Color Textured Image Retrieval By Combining Texture And Color Features "European Signal Processing Conference (EUSIPCO-2012), Bucharest : Romania (2012)".

 ISBN 978-80-86943-76-3