Light Field Retrieval In Compressed Domain

[(a)]Lakhdar BELHALLOUCHE [(a)]Kamel BELLOULATA [(b)]Kidiyo KPALMA

Lakhdar_belhallouche@hotmail.fr Kamel.Belloulata@USherbrooke.ca kidiyo.kpalma@insa-rennes.fr

[(a)]Université Djillali Liabés [(b)]INSA Rennes

ABSTRACT

In this paper, we present a novel approach for light field retrieval in the compressed 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 consider image. We use texture and color features to characterize the object image; the similarity is measured by matching histograms of a pair of images. The experimental results and comparisons show the performance of the proposed technique.

Keywords

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

1. INTRODUCTION

The rapid advance of digital technologies has many improved 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) or scientific (medical applications industrial, cultural heritage). The easy 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 search 3D models engines used 2D shapes drawing by user as a query image. One of the most important approaches is to search relevant 3D models efficiently and correctly by querying from a database models, in other words, it proposed to match the input 3D model to each one in the database [1]. The proposed approach in [2] is based on 20 silhouettes characterizing. This method represents the object in 20 different locations on the sphere. Chen et al [1] propose to match 3D objects based on view based similarity measure. Other geometry based retrieval methods are based on matching 3D models according to geometric distribution, topology structure and curvature of a patch [3].

These ones are able to 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 projection. Ohbuchi et al, for instance propose characterizing scheme of each view image using the SIFT algorithm [4].

The local features were then integrated into a histogram using a bag of features approach to retrieval.

Light field is a structure based-image representation for interactive visualization for any new point of view.

A mechanism for efficient compression based on wavelet transform, can be used to reduce the cost of storage light field while maintaining a realistic visualization. Therefore, by combining the two operations of compression and indexing, we can extract achieve retrieval light field directly in the compressed domain.

In this paper, we describe an image based light field retrieval, our system use an approximated light field representation proposed in [5], this presentation considers only 20 captured key views from a fixed set of positions on the sphere. Each view object is firstly quadtree decomposed into homogeneous blocks, two regions can be identified: background and the object. We secondly convert the object into YCbCr space, each image component is then transformed using wavelet transform. We finally construct texture and color features from the low coefficient wavelet transform, these features are organized into a histogram to represent the object. The retrieval light field step is based on similarity measure based on Euclidean disctance measure between the query view and candidate views.

The rest of this paper is organized as follows. We first describe used data acquisition process [4]. Next we describe our method for convert and transform of the light field. We then explain the texture and color features construction. Finally, we present and analyse the resultsfrom our expreriments and provide a conclusion.

2. Data acquisition system

The use of such system allows taking into consideration all rotations, scaling and moving of the object. Our indexing system can be robust to the conditions of rotation, displacement and scale change (Figure 1). Ameesh proved that this acquisition system of the light field offers best possible correlation alignment between the models light field

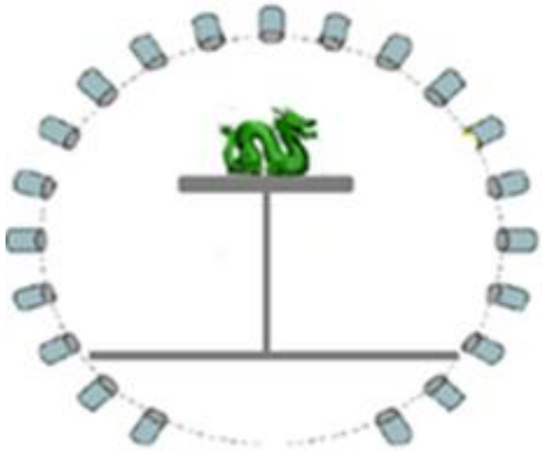

Figure 1. acquisition system [5]

3. Compression scheme

3.1. Image quadtree decomposition

Color image is firstly converted from RGB to YCbCr (figure 2).

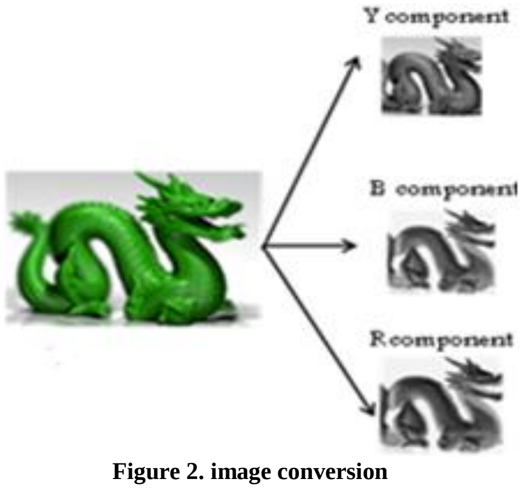

Figure 2. image conversion

The image is then successively decomposed into quadrant depending on the complexity of the bock. While the sub image is not a homogenous block, the decomposition operation continues. At the end we have a set of homogenous block (figure 3). A sub image is called a homogeneous block if the gray-level of each of the pixels in the block is varied in some specified constant. In our work, all used image must be M*N square image. Although the images have the texture and color features, we decompose the image, based on grey level only. This is advantageous in the retrieval system.

In our case, we have an image data base download from [7], consider the approach of acquisition explained above we consider only the objects with 18° rotations angle. Obtained views represent the light field of the object.

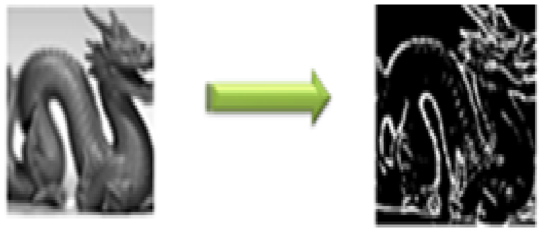

Figure 3. image quadtree decomposition

3.2. Image compression using wavelet transform

A light field, such as we use, is a structured set of images of an object from various viewpoints. These viewpoints are coded using the biorthogonal Cohen–Daubechies–Feauveau 9/7 wavelet transform. This wavelet transform is popular for image compression. Note that due to the irrational coefficients of the 9/7 wavelet, the intra-view transform is in general not reversible. Nevertheless, for lossy compression this irreversibility in the intra-view transform has only minimal impact on compression efficiency. [8]

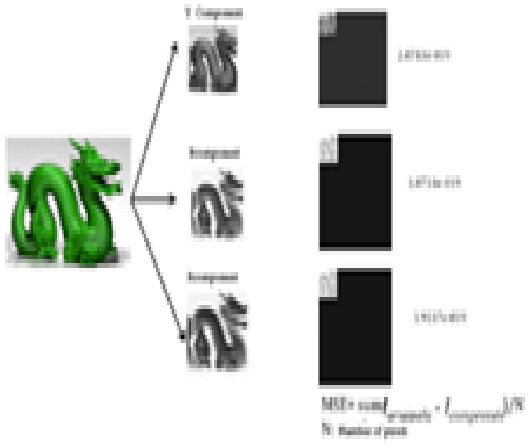

Figure 4. view compression using Cohen–Daubechies–Feauveau 9/7 wavelet transform

4. View light field indexing

Our application was based on low wavelet coefficients transform of different viewpoints light field. The base framework of our light field indexing, starts by choice 20 views of the object during acquisition step, each view is then transformed using DWT. The low-resolution coefficients are used to construct texture and color feature.

4.1. Texture feature construction

We now present the first method to construct the texture feature. For the moment, consider the above image conversion which gives three image components YC_bC_r. Each transformed component is characterized using a texture feature. We firstly construct the co-occurance matrix of each component. Three textural features are computed from each co-occurrence matrix by the following equations:

Contrast feature: it represent the contrast distance between each pixel and his surround.

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

Energy feature: it is the squared addition of the values of the co-occurance matrix.

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

Homogeneous feature: it measures the distribution of the co-occurance matrix elements around the diagonal. $\sum_{i,j} \frac{P(i,j)}{1+|i-j|}$

4.2. Color feature construction

The second phase of features construction performs mean grey level calculate to characterize the color attribute of each component image. So, three color components mean, are computed as the color features of each block (figure 5).

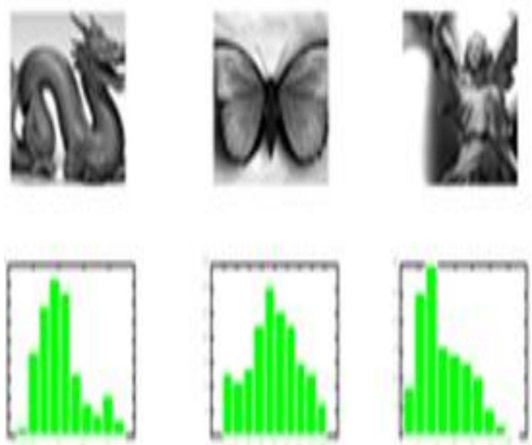

Figure 5. Color feature construction

Once all the features have been extracted, every homogeneous block is represented by a six-element vector as <Y, C_b, C_r, Contrast, Energy, Homogeneous> (Figure 6).

The value of each of the six-element is normalized between 0 and 1 [6]. And then we quantize vectors elements after normalization.

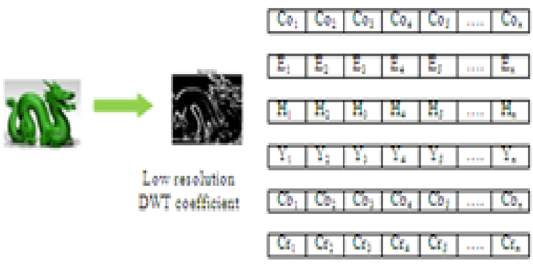

Figure 6. color and texture vectors construction

4.3. Histogram generation

The texture histogram represents the frequencies of all the texture vectors. The histogram is then quantized into M bins such that:

H_T= {h (b1) T, h (b2) T ….h (bM) T}. M = 32 bins.

h(bi) : is the frequency of the texture vector in bin bi.

The same method is used to construct the color histogram (H_C) [The Statistical Quantized Histogram].

4.4. Similarity Measurements

As many of current Retrieval approaches, our similarity measurement method is based on Euclidian distance on the extracted feature set as a similarity function.

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

Where HCi and HQi be the feature histograms of candidate image C and Query image Q respectively with size 'n'.lake images in the data base.

5. Experimental Results

The proposed algorithm is tested by a database of images. The database consists of 100 images having 5 image categories; each category contains 20 view objects. 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 light field views.

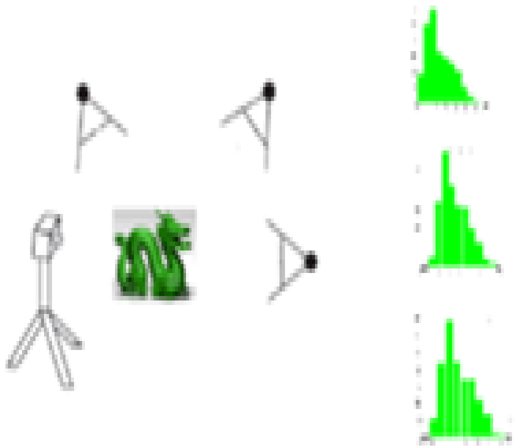

Figure 7. characterization of the image under different rotation conditions

The resulted Euclidian distances between the query image and the database images feature histograms are used to calculate the precision and recall:

$\text{Precision} = \frac{\text{number of relevant images retrieved}}{\text{total of images retrieved}}$

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

The two graphs above show the limitations of the first method, which does not take into account the nature of the light field, on the variation of rotation of the object in order to overcome this problem, we introduced the concept of view based light field retrieval.

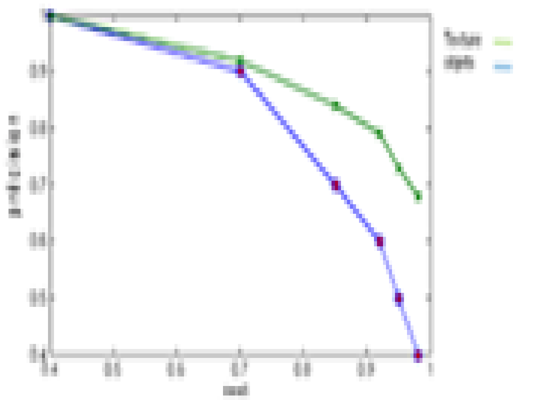

Figure 8. Evaluation of the algorithm using two different image data base

The graph below shows that this has greatly improved the results of our algorithm.

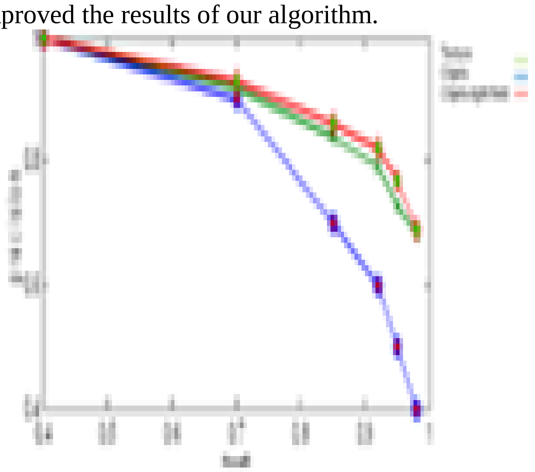

Figure 9. the effect of the light field on our retrieval system

A number of experiments were performed to evaluate the performance of our proposed approach and its variants.

The first shows the effect of choice views on the retrieval efficiency. As shown in Figure 9, the retrieval performance improves (retrieval score decreases) as we use the object descriptor. For the retrieval light field views based characterizing has the best retrieval rate.

6. CONCLUSION

In this work we have addressed the problem of light field access by the constitution of system of indexing and image retrieval in the compressed domain. The proposed solutions were evaluated in the context of image based light field retrieval. The themes and the methods used are proposed to reduce the computational complexity and limit the length of descriptors. The introduction of the notion of robustness allows our approach more robust to conditions rotation and translation.

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