Image Retrieval Using Lifting Wavelet Filters

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Abstract: - In this paper, we propose a new content-based image retrieval system based on lifting wavelet filters. Lifting wavelet filters include controllable free parameters. A new similarity measure of images is introduced using the free parameters computed from the high frequency components of images. Using this measure, matching of query image with template images is done. Next, the query image is compared with the subimages lying under the category of template image similar to the query image using their histograms. A clustering method for subimages is also proposed. Finally, simulation results are given.

Key-Words: - Image retrieval, Lifting wavelet filters, Similarity, Subimage extraction, Clustering, Matching

1 Introduction

The goal of content-based image retrieval (CBIR) systems is to search images similar to a query image given by users. So far, many researchers have developed various CBIR systems [2,5]. The method in [2] uses features of an image such as color histograms, texture and shape. VisualSeek [5] employs the back-projection technique to extract color-regions in an image. Recently, wavelet transform has received much attention as a tool for developing CBIR systems [1,3,4]. In Jacob [3], multiresolution analysis of Haar wavelet transform has been used to realize fast image querying. WARLUS [4] combines the sliding windows within the image with Haar wavelet transform.

In this paper, we propose a new CBIR system based on lifting wavelet filters. Lifting wavelet filters are biorthogonal wavelet filters containing controllable free parameters [6].

Usually, natural images contain several kinds of same subimages whose locations are not fixed. Therefore, the matching of natural images themselves does not succeed. So we need to extract subimages from the natural image before carrying out pattern matching. In our papers [7,8,9,10], we proposed a novel method for extracting subimages from a large reference image. The method uses the learning of real- and integer-type lifting wavelet filters.

This paper proposes a simple subimage extraction method using biorthogonal wavelet filters and develops an image retrieval system for extracted subimages. To measure the similarity of two subimages, we compute free parameters included in the lifting wavelet decomposition filter so that the high frequency components of one image coincide with those of the other one. If the computed free parameters are close to zero, two images are similar. Using this criterion, we measure the distance between a template image and the extracted subimages and cluster all the subimages. The matching of a query image with a template image is done using the same criterion. However, it is not efficient to match the query image directly with the subimages lying under the category of template image. So we make histograms of all the subimages and the query image and, compare the histograms.

This paper is organized as follows. In Section 2, we describe a subimage extraction method. Section 3 introduces a similarity measure of images, in which lifting wavelet filters are used. In Section 4, we describe a clustering method for subimages and a matching algorithm. Section 5 presents a simulation. We close in Section 6 with concluding remarks and future work.

2 Subimage Extraction

Object images we want to retrieve are assumed to contain many large high frequency components. To realize fast retrieval of object images, we extract in advance square domains where large high frequency components concentrate as candidates which we call subimages from now on. In this paper, such high frequency components are computed by applying the biorthogonal wavelet filters to the base image.

2.1 Biorthogonal Wavelet Filters

The wavelet filters $h^{old}_{k,l}, \tilde{h}^{old}_{k,l}, g^{old}_{m,l}$ and $\tilde{g}^{old}_{m,l}$ are said to be biorthogonal wavelet filters if they satisfy the conditions

$$\sum_l h^{old}_{k,l}\tilde{h}^{old}_{k',l} = d_{k,k'}, \qquad \sum_l g^{old}_{m,l}\tilde{h}^{old}_{k,l} = 0,$$
$$\sum_l h^{old}_{k,l}\tilde{g}^{old}_{m,l} = 0, \qquad \sum_l g^{old}_{m,l}\tilde{g}^{old}_{m',l} = d_{m,m'}, \tag{1}$$

where $d_{k,k'}$ denotes the Kronecker's delta symbol. Here $\tilde{h}^{old}_{k,l}$ and $\tilde{g}^{old}_{m,l}$ stand for low-pass and high-pass decomposition filters, and $h^{old}_{k,l}$ and $g^{old}_{m,l}$ represent low-pass and high-pass reconstruction filters, respectively.

We denote a base image by $C^1_{i,j}$. Applying the filters $\tilde{h}^{old}_{k,l}$ and $\tilde{g}^{old}_{m,l}$ both in horizontal and vertical directions to the image $C^1_{i,j}$, we can decompose $C^1_{i,j}$ into four kinds of components as

$$\hat{C}^0_{k,k'} = \sum_{i,j} \tilde{h}^{old}_{k,i}\tilde{h}^{old}_{k',j}C^1_{i,j}, \tag{2}$$

$$\hat{D}^0_{k,m} = \sum_{i,j} \tilde{h}^{old}_{k,i}\tilde{g}^{old}_{m,j}C^1_{i,j}, \tag{3}$$

$$\hat{E}^0_{m,k} = \sum_{i,j} \tilde{g}^{old}_{m,i}\tilde{h}^{old}_{k,j}C^1_{i,j}, \tag{4}$$

$$\hat{F}^0_{m,m'} = \sum_{i,j} \tilde{g}^{old}_{m,i}\tilde{g}^{old}_{m',j}C^1_{i,j}. \tag{5}$$

Here $\hat{C}^0_{k,k'}$ is the low frequency component and, $\hat{D}^0_{k,m}$ $\hat{E}^0_{m,k}$, and $\hat{F}^0_{m,m'}$ are the high frequency components in horizontal, vertical and diagonal directions, respectively, of the image. We call equations (2), (3), (4) and (5) wavelet decomposition formulae.

Conversely, by virtue of the biorthogonal conditions (1), we can restore the original image $C^1_{i,j}$ from $\hat{C}^0_{k,k'}, \hat{D}^0_{k,m}, \hat{E}^0_{m,k}$, and $\hat{F}^0_{m,m'}$ by the formula

$$C^1_{i,j} = \sum_{k,k'} h^{old}_{k,i}h^{old}_{k',j}\hat{C}^0_{k,k'} + \sum_{k,m} h^{old}_{k,i}g^{old}_{m,j}\hat{D}^0_{k,m} + \sum_{m,k} g^{old}_{m,i}h^{old}_{k,j}\hat{E}^0_{m,k} + \sum_{m,m'} g^{old}_{m,i}g^{old}_{m',j}\hat{F}^0_{m,m'}. \tag{6}$$

We call (6) a wavelet reconstruction formula. The formulas (2), (3), (4), (5) and (6) imply that the base image $C^1_{i,j}$ is equivalent to $\{\hat{C}^0_{k,k'}, \hat{D}^0_{k,m}, \hat{E}^0_{m,k}, \hat{F}^0_{m,m'}\}$.

2.2 Subimage Extraction Algorithm

Using (3) and (4), we compute the high frequency components $\hat{D}^0_{k,m}$ and $\hat{E}^0_{m,k}$. In this paper, $\hat{F}^0_{m,m'}$ is not used to extract subimages because $\hat{D}^0_{k,m}$ and $\hat{E}^0_{m,k}$ have enough information about large high frequency components of the base image. We select a square domain and sum up the absolute values of each of $\hat{D}^0_{k,m}$ and $\hat{E}^0_{m,k}$ in the domain. Next, we find a square domain in which the total value exceeds a certain threshold. An example of subimage extraction is shown in Fig. 1.

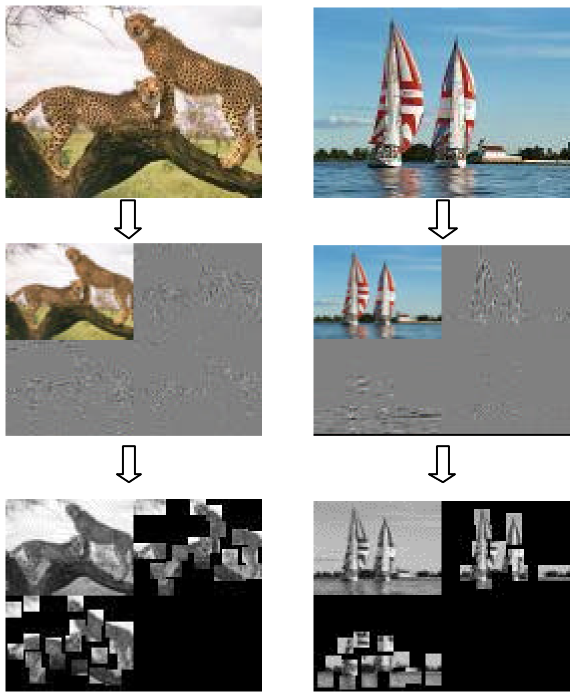


Figure 1. Subimage extraction.

Our subimage extraction algorithm involves the following steps.

(i) Compute $\hat{D}^0_{k,m}$ and $\hat{E}^0_{m,k}$ as given in (3) and (4).

(ii) Sum up the absolute values of each of $\hat{D}^0_{k,m}$ and $\hat{E}^0_{m,k}$ in a given square domain.

(iii) Find square domains in which the total values exceed a certain threshold.

3 Similarity of Images

We propose a method for measuring a similarity of two images. Our method uses lifting wavelet filters.

The lifting wavelet filters are biorthogonal wavelet filters including free parameters. First, we apply biorthogonal wavelet filters to one of the two images to compute two types of high frequency components, and to the other image to compute one low type and two types of high frequency components. Next, we determine the free parameters in the lifting wavelet filters so that the new high frequency components obtained by lifting up the high frequency components of the latter image are equal to those of the former image. We measure the similarity of the two images by checking whether the vector having the computed parameters as its elements is close to zero vector or not.

3.1 Lifting Wavelet Filters

We denote old biorthogonal wavelet filters by $h_{k,l}^{old}, \tilde{h}_{k,l}^{old}, g_{m,l}^{old}$ and $\tilde{g}_{m,l}^{old}$. Lifting wavelet filters are given by

$$\begin{aligned} h_{k,l} &= h_{k,l}^{old} + \sum_m \tilde{s}_{k,m} g_{m,l}^{old}, \\ \tilde{h}_{k,l} &= \tilde{h}_{k,l}^{old}, \\ g_{m,l} &= g_{m,l}^{old}, \\ \tilde{g}_{m,l} &= \tilde{g}_{m,l}^{old} - \sum_k \tilde{s}_{k,m} \tilde{h}_{k,l}^{old}, \end{aligned} \qquad (7)$$

where $\tilde{s}_{k,m}$ denote free parameters. It has been proved by Sweldens [6] that the lifting wavelet filters are also biorthogonal.

3.2 Computaion of Free Parameters

We denote a subimage also by $C_{i,j}^1$ and compute high frequency components in horizontal and vertical directions of $C_{i,j}^1$ by using the lifting wavelet filter (7). Using the symbols $\tilde{s}_{k',m}^d$ and $\tilde{s}_{k',m}^e$ to distinguish free parameters occurring in both directions, we represent new high frequency components as

$$D_{k,m}^0 = \hat{D}_{k,m}^0 - \sum_{k'} \tilde{s}_{k',m}^d \hat{C}_{k,k'}^0, \qquad (8)$$

$$E_{m,k}^0 = \hat{E}_{m,k}^0 - \sum_{k'} \tilde{s}_{k',m}^e \hat{C}_{k',k}^0, \qquad (9)$$

where $\hat{C}_{k,k'}^0, \hat{D}_{k,m}^0$ and $\hat{E}_{m,k}^0$ are low and two types of high frequency components for the former image.

Let $\hat{D}_{k,m}^{0,t}$ and $\hat{E}_{m,k}^{0,t}$ denote the high frequency components in horizontal and vertical directions for the latter image $C_{i,j}^{1,t}$. Equations for determining free parameters $\tilde{s}_{k',m}^d$ and $\tilde{s}_{k',m}^e$ are essentially given by

$$\hat{D}_{k,m}^0 - \sum_{k'} \tilde{s}_{k',m}^d \hat{C}_{k,k'}^0 = \hat{D}_{k,m}^{0,t}, \qquad (10)$$

$$\hat{E}_{m,k}^0 - \sum_{k'} \tilde{s}_{k',m}^e \hat{C}_{k',k}^0 = \hat{E}_{m,k}^{0,t}. \qquad (11)$$

For simplicity, we restrict the number of each of $\tilde{s}_{k',m}^d$ and $\tilde{s}_{k',m}^e$ to five, and write as

$$\tilde{s}_{m-2,m}^d, \tilde{s}_{m-1,m}^d, \cdots, \tilde{s}_{m+2,m}^d,$$
$$\tilde{s}_{m-2,m}^e, \tilde{s}_{m-1,m}^e, \cdots, \tilde{s}_{m+2,m}^e.$$

Since the number of unknown parameters is five for each of $\tilde{s}_{k',m}^d$ and $\tilde{s}_{k',m}^e$, we need five equations for each. One of the five equations for $\tilde{s}_{k',m}^d$ is

$$\sum_{k'=m-2}^{m+2} \tilde{s}_{k',m}^d = 0 \qquad (12)$$

which implies that $D_{k,m}^0$ becomes high frequency components. The remaining four equations are (10) , the equation obtained by replacing k by k+1 in (10), and the two equations obtained by replacing m by m+1 in the previous two equations. Writing them in matrix form, we get

$$\begin{bmatrix} \hat{C}_{k,m-2}^0 & \cdot & \hat{C}_{k,m+2}^0 \\ \hat{C}_{k,m-1}^0 & \cdot & \hat{C}_{k,m+3}^0 \\ \hat{C}_{k+1,m-2}^0 & \cdot & \hat{C}_{k+1,m+2}^0 \\ \hat{C}_{k+1,m-1}^0 & \cdot & \hat{C}_{k+1,m+3}^0 \\ 1 & \cdot & 1 \end{bmatrix} \begin{bmatrix} \tilde{s}_{m-2,m}^d \\ \tilde{s}_{m-1,m}^d \\ \tilde{s}_{m,m}^d \\ \tilde{s}_{m+1,m}^d \\ \tilde{s}_{m+2,m}^d \end{bmatrix} = \begin{bmatrix} \hat{D}_{k,m}^0 - \hat{D}_{k,m}^{0,t} \\ \hat{D}_{k,m+1}^0 - \hat{D}_{k,m+1}^{0,t} \\ \hat{D}_{k+1,m}^0 - \hat{D}_{k+1,m}^{0,t} \\ \hat{D}_{k+1,m+1}^0 - \hat{D}_{k+1,m+1}^{0,t} \\ 0 \end{bmatrix} \qquad (13)$$

Solving this system, we obtain the parameters $\tilde{s}_{k',m}^d$.

In the same way as for $\tilde{s}_{k',m}^d$, we get the following equations for the computation of $\tilde{s}_{k',m}^e$

$$\begin{bmatrix} \hat{C}_{m-2,k}^0 & \cdot & \hat{C}_{m+2,k}^0 \\ \hat{C}_{m-1,k}^0 & \cdot & \hat{C}_{m+3,k}^0 \\ \hat{C}_{m-2,k+1}^0 & \cdot & \hat{C}_{m+2,k+1}^0 \\ \hat{C}_{m-1,k+1}^0 & \cdot & \hat{C}_{m+3,k+1}^0 \\ 1 & \cdot & 1 \end{bmatrix} \begin{bmatrix} \tilde{s}_{m-2,m}^e \\ \tilde{s}_{m-1,m}^e \\ \tilde{s}_{m,m}^e \\ \tilde{s}_{m+1,m}^e \\ \tilde{s}_{m+2,m}^e \end{bmatrix} = \begin{bmatrix} \hat{E}_{m,k}^0 - \hat{E}_{k,m}^{0,t} \\ \hat{E}_{m+1,k}^0 - \hat{E}_{m+1,k}^{0,t} \\ \hat{E}_{m,k+1}^0 - \hat{E}_{m,k+1}^{0,t} \\ \hat{E}_{m+1,k+1}^0 - \hat{E}_{m+1,k+1}^{0,t} \\ 0 \end{bmatrix} \qquad (14)$$

The solution of these equations yields the parameters $\tilde{s}_{k',m}^e$. Similar parameters are computed for each subimage.

3.3 Similarity of Images

We define a similarity measure of images. Using the parameters $\tilde{s}^{d}_{k',m}$ and $\tilde{s}^{e}_{k',m}$ computed in the previous section, let us introduce two kinds of distances between $C^{1}_{i,j}$ and $C^{1,t}_{i,j}$ as

$$Q^{t}_{d}(C^{1}_{i,j}, C^{1,t}_{i,j}) = \sum_{m} \sum_{k=m-2}^{m+2} \left(\tilde{s}^{d,t}_{k,m}\right)^2, \qquad (15)$$

$$Q^{t}_{e}(C^{1}_{i,j}, C^{1,t}_{i,j}) = \sum_{m} \sum_{k=m-2}^{m+2} \left(\tilde{s}^{e,t}_{k,m}\right)^2. \qquad (16)$$

We assume that $C^{1}_{i,j}$ is similar to $C^{1,t}_{i,j}$ if (15) or (16) is close to zero.

4 Image Retrieval

In this section, we describe a method for clustering subimages extracted from the database of images and a method for matching a query subimage with the subimages.

4.1 Clustering

By using our subimage extraction method described in Section 2.2, subimages are extracted from the database of images. We first give a set of template images. For each template image $C^{1,t}_{i,j}$ and each subimage $C^{1}_{i,j}$, free parameters $\tilde{s}^{d}_{k',m}$ and $\tilde{s}^{e}_{k',m}$ are computed using the method given in Section 3.2. The clustering of the extracted subimages is done by measuring the distances between $C^{1}_{i,j}$ and $C^{1,t}_{i,j}$. If this clustering fails, we replace the old set of template images by a new set of template images. For this new set and the detected subimages, the above procedure is carried out. This process is repeated until the clustering is complete.

First, a query image is matched with the template images based on the similarity criterion proposed in Section 3.3. The next step is to match the query image with the subimages in the categories connected with the selected template image. However, the latter matching is time consuming. So we make histograms of the elements of a vector consisting of computed free parameters for each subimage and match a histogram for a query image with these histograms to realize fast matching.

We summarize our clustering algorithm as follows.

(i) Extract subimages from the database of images.

(ii) Give a set of template images.

(iii) For each pair of template image and subimage, compute free parameters using the method of Section 3.2.

(iv) Cluster all the subimages by measuring the distances (15) and (16).

(v) If the clustering fails, prepare a new set of template images and go to step (iii).

(vi) If the clustering succeeds, make histograms of the elements of a vector of computed free parameters.

Fig. 2 shows an overview of clustering algorithm.

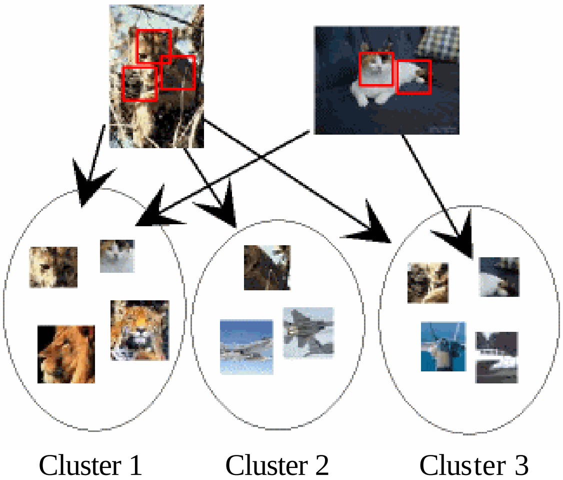


Figure 2: Overview of our clustering algorithm.

4.2 Matching

The first step of matching is a computation of free parameters for a query image and the template image following the method given in Section 3.2. The next task is to compute the distances between the query and the template images using the formulas (15) and (16), and to choose a template image having the least distance from the query image. Finally, we compare a histogram of the query image with those of the subimages connected with the selected template image. The difference between the histograms is measured using Euclidean distance. This matching method is faster than that of comparing directly computed free parameters. Fig.3. shows an overview of matching algorithm.

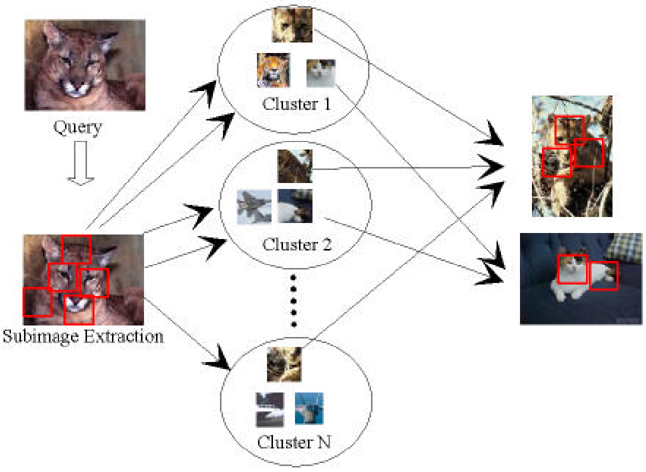


Figure 3: Overview of our matching algorithm.

5 Simulation

In order to evaluate the performance of our image retrieval system, we give simulation using a natural image dataset obtained from various web sites. The dataset contains 2674 images stored in JPEG format. Since the images have different size, we changed the horizontal or vertical length, whichever is longer, of the image into 128, keeping the aspect ratio fixed. From all such images, we extract subimages of size 16x16 each by the method of Section 2.2. The number of subimages was about 50 thousand.

We gave a set of 8 template images and tried to cluster all the subimages, but failed to cluster. Finally, we succeeded to cluster the subimages when the following 32 texture images were used. Fig. 4 illustrates parts of the template images.

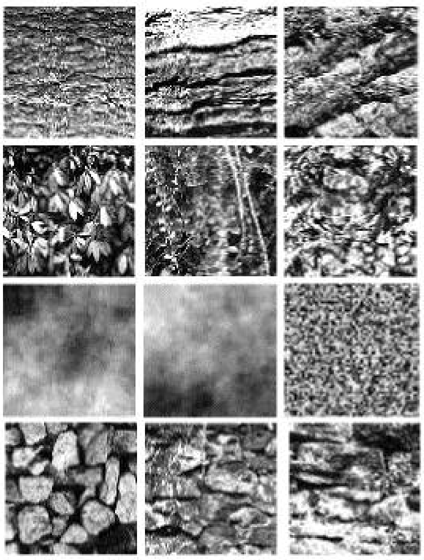
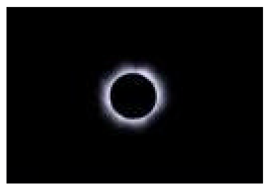


Figure 4: Template images.

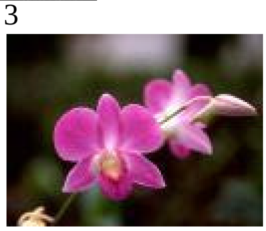
Given a query image, we chose a template image close to the query image and compared the histogram of the query image with those of the subimages. We show two simulation results in Fig.5. It is seen that when a natural image was input, natural images related to the input image have been extracted, although the template images are texture images which are unrelated to the natural images.

Query 1

Query 2



Query 3



Query 4

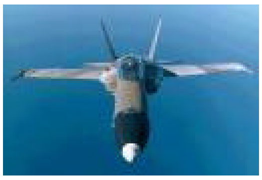



Figure 5: Images founded by our method.

6 Conclusion

In this paper, we proposed an image retrieval method based on lifting wavelet filters. The main contribution of our method is to use two kinds of measures. One is based on the size of free parameters which are computed for two images using the lifting wavelet filters. The other uses the histograms of free parameters computed for a query image and clustered subimages. The comparison of histograms is faster than that of the computed free parameters. Another advantage of our approach is to be able to cluster automatically subimages extracted from a large database. In future, we want to use low frequency components as well as high frequency components of an image for mesuaring the similarity of images.

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