Abstract — One of the important tasks in most of Content Based Image Retrieval (CBIR) systems is similarity matching. Similarity matching requires distance computation of feature vectors for each candidate image in the image database. Conventional algorithms based on exhaustive search are highly time consuming and inefficient. With rapid increase in database size, there is a growing need of a fast and efficient retrieval system. Multiresolution data-structure based approach provides a good solution to above problem but there is still scope for improvement. In this paper we propose a wavelet based multiresolution data-structure algorithm for faster image search. The proposed approach reduces the number of computations by about 50% over multiresolution data-structure algorithm. In the proposed approach we reuse the information obtained at lower resolution levels for similarity matching at higher resolution levels. This algorithm also saves disk storage space by about 50% over multiresolution data-structure approach. The proposed approach can be easily combined with existing algorithms for further performance enhancement. In this paper we use the proposed approach to match similarity between luminance histograms for image retrieval.

keywords—Content based image retrieval, fuzzy histogram, multiresolution histogram, wavelet histogram, feature matching.

1. INTRODUCTION

Content based indexing and retrieval have a prominent role to play in research on digital database. A rapid growth in number and size of images in databases has created a strong need for more efficient search and retrieval systems to exploit the benefit of this large amount of information. CBIR finds abundant application in a wide range of areas like digital libraries, architecture, crime prevention, digital signature matching etc. Traditional systems use text based manual annotation for retrieval, but as the number of candidate images in database increases text based system becomes highly inefficient. The main problems being tremendous amount of manual labour required to annotate the images and few keywords are not sufficient to describe an image. This limits the usefulness of the system [2].

So there is a growing need for a system which can retrieve images based on low level features like color, texture, shape etc. CBIR systems rely on similarity matching of feature vectors of query image with database images. Simplest approach for color similarity matching is pixel luminance matching. But pixel matching is a computationally intensive and will be very time consuming. Further this approach is highly sensitive to noise and small distortions like displacement and rotation. So we need a feature of image which is invariant to noise and small distortions and is not computationally intensive. Histograms are widely used as feature of images since they are robust to small distortions and histogram matching is very easy to implement. Further histogram matching is not an intensive job.

In order to find most similar matches for a query image according to a given similarity measure, the exhaustive search algorithm will have to be performed on all the candidate images. The cost of computation for exhaustive similarity matching is very high. An interesting algorithm based on MultiResolution Histogram (MRH) [3] matching has been proposed by Song, Kim and Ra. This algorithm discards unworthy candidate images at lower resolution by calculating the lower bound on the distance between feature vectors of query image and candidate images in database. The distance at lower resolution level is compared with \( d_{max} \). If \( d \leq d_{max} \), then distance is computed at higher level, else this image is discarded.

To reduce the computational cost further, we extend this multiresolution histogram technique to multiresolution wavelet histogram matching technique. We also employ this technique to fuzzy histograms [4][1]. The proposed technique provides a faster retrieval system by reducing the computational cost to about half, while the retrieval performance is quite comparable to that of multiresolution technique. Further the proposed structure reduces memory overheads by around 50%. In the next section, we introduce the proposed wavelet based algorithm. Section 3 describes fuzzy histograms. The computational cost analysis is done in section 4. The experimental results are given in section 5, and section 6 concludes this paper.
We have proposed an efficient wavelet based multiresolution histogram matching technique for fast and exhaustive image search. To reduce the computational complexity we employ a wavelet pyramid structure of image color histogram. Let us take a \(2^K\) bin histogram \(X\), then wavelet pyramid structure is a sequence of histograms \((X_f, X_h, X_f, X_h, \ldots, X_h, X_f)\), where \(X_f\) and \(X_h\) are low frequency and high frequency components of wavelet transform of \(X\), \(X_f\) and \(X_h\) are low frequency and high frequency components of wavelet transform of \(X_f\) and so on. This can be stated as

\[
[X_f^{K-1}, X_h^{K-1}] = \text{dwt}(X) \quad (1)
\]

\[
[X_f^k, X_h^k] = \text{dwt}(X_f^{k+1}) \quad \text{for } 1 \leq k \leq K-2. \quad (2)
\]

The number of bins in \(X_f^k\) and \(X_h^k\) are \(2^k\). Now for a given query histogram \(Q\), we will compute the L1-norm distance between \(Q_f^k\) and \(X_f^k\). We can approximate \(d(Q_f^k, X_f^k)\) to sum of \(d(Q_f^{k-1}, X_f^{k-1})\) and \(d(Q_h^{k-1}, X_h^{k-1})\), i.e.

\[
d(Q_f^k, X_f^k) = d(Q_f^{k-1}, X_f^{k-1}) + d(Q_h^{k-1}, X_h^{k-1}), \quad (3)
\]

where \(d(a,b)\) is L1 distance between vectors "a" and "b". In this way to compute distance at some resolution level \(k\), we can reuse the previously computed distance at resolution level \(k-1\). This reduces the computational cost by around 50%. We pre-compute the wavelet pyramid structure of all the candidates in image database and store it beforehand as feature database. To search for the best matches of a query in a database of \(N\) images, we will compute the feature vector distance of query image and each candidate images at minimum resolution level (2 bin level). We then sort these distances and keep \% of the \(N\) images with least distances and discard the rest. For these \((nN/100)\) images we compute the distance at 4 bin level and again keep \% of these \((nN/100)\) images with least distances and so on. Finally at full resolution we will be left with very few candidate images. We compute the full resolution distance for these candidates and present the M images with least distance as best matches.

The feature database consists of 2 bin low frequency histogram and 2 bin - 128 bin high frequency histograms. So the total disk space required is \((2 + 2 + 4 + 8 + 16 + 32 + 64 + 128)N*4 = 4*256N\) bytes. In the case of MRH we will need \((2 + 4 + 8 + 16 + 32 + 64 + 128 + 256)N*4 = 4*512N\) bytes (assuming 4 bytes are required to store one bin content). This saves the disk space requirement by 50%.

**Calculation of wavelet pyramid**

In the proposed approach the wavelet histogram pyramid is precomputed for each candidate image in database and stored beforehand. For a given query, wavelet pyramid is computed first. To compute this wavelet pyramid we have to calculate 7 discrete wavelet transforms[5]. This computation is negligible in comparison to wavelet histogram matching computation since a single histogram matching at 256 bins requires \(256*3\) absolute operations and \(511*3\) additions[3]. We need to store only high frequency components of wavelet histograms and the 2 bin low frequency histogram. This gives a hidden advantage as the memory requirement reduces by about 50%.

**3. FUZZY HISTOGRAM**

In a luminance color histogram two similar colors will be treated as identical provided they are allocated to same bin. On the other hand two colors will be considered totally different if they fall into two different bins even though they might be very similar to each other and fall into adjacent bins. This makes color histogram sensitive to noisy interference such as illumination changes and quantization errors. Many researchers have proposed Fuzzy Histograms. Fuzzy Color Histogram(FCH)[1] proposed by Ju Han and J K K M considers the color similarity information by spreading each pixel's total membership value to all the histogram bins. This spreading can be achieved by convolving the normal color histogram with a Gaussian function[4].

\[
h_f(c) = h(c) * g(c)
\]

where \(g(c)\) is a Gaussian function and \(h(c)\) is normal color
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histogram. Fig 2 shows a fuzzy membership function \( g(c) \) to spread the contribution of a pixel to neighboring bins. We have explored this for our proposed wavelet based multiresolution histograms. We construct a sum pyramid structure as described in previous section, then we convert all the histograms to fuzzy histograms. After this we take wavelet transform of these fuzzy histograms. Matching fuzzy histograms improves the performance as shown in experimental results.

4. COMPUTATIONAL COST ANALYSIS

For a image database with \( N \) candidates, if we do exhaustive query search with a 256 bin histogram and \( L_1 \)-norm distance measure then the computational requirements are given below:

Number of absolute operations performed = \( 256 \times 3N \)

Number of additions performed = \( 511 \times 3N \)

MultiResolution Histogram

Now if we use multiresolution histogram algorithm(MRH)[3] and keep \( r \% \) of images at each resolution level and use \( L_1 \)-norm distance measure then the computational requirements are as follows:

Number of absolute operation = \[
\left\{ \begin{array}{ll}
2N & \text{for } r \neq 0.5 < 1; \\
48N & \text{for } r = 0.5
\end{array} \right.
\]

Number of additions = \[
\left\{ \begin{array}{ll}
12N(\frac{2N}{(r-1)^3}) - N(\frac{s-1}{r-1}) & \text{for } r \neq 0.5 \\
94N & \text{for } r = 0.5
\end{array} \right.
\]

Wavelet Based MRH

Now for same \( r \) and \( L_1 \)-norm distance if we use proposed wavelet histogram matching algorithm the computational requirements are given below:

Number of absolute operation = \[
\left\{ \begin{array}{ll}
N(1 + (\frac{2N}{(r-1)^3})) \times 3 & \text{for } r \neq 0.5 \\
27N & \text{for } r = 0.5
\end{array} \right.
\]

Number of additions = \[
\left\{ \begin{array}{ll}
6N(1 + (\frac{2N}{(r-1)^3})) & \text{for } r \neq 0.5 \\
54N & \text{for } r = 0.5
\end{array} \right.
\]

Table 1. Computations for Wavelet Based MRH(WMRH) and MRH

<table>
<thead>
<tr>
<th>( r/100 )</th>
<th>MRH</th>
<th>WMRH</th>
<th>MRH</th>
<th>WMRH</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>48N</td>
<td>27N</td>
<td>94N</td>
<td>54N</td>
</tr>
<tr>
<td>0.6</td>
<td>99N</td>
<td>52.5N</td>
<td>197.5N</td>
<td>105N</td>
</tr>
<tr>
<td>0.7</td>
<td>206.4N</td>
<td>106.2N</td>
<td>409.5N</td>
<td>212.4N</td>
</tr>
<tr>
<td>0.8</td>
<td>419.5N</td>
<td>212.7N</td>
<td>835N</td>
<td>425.4N</td>
</tr>
<tr>
<td>0.9</td>
<td>819N</td>
<td>412.5N</td>
<td>1632N</td>
<td>825N</td>
</tr>
</tbody>
</table>

From Tables 1, we can see that using the proposed approach the number of computation have been reduced by 43% for \( r = 50 \%. \) Retrieval cost for fuzzy histograms is same as that of wavelet based multiresolution histograms. Computation required in fuzzification of normal histograms can be neglected.

5. EXPERIMENTAL RESULTS

For evaluating performance we used a database containing 10,000 images. The database includes various types of images like birds, houses, natural scenes, flags, sports cars etc. 60 sets of around 15 similar looking images were selected from the database for performance evaluation. For each of these sets and for every member of a set 50 images were retrieved from the database. We use 256 bin histogram and \( L_1 \)-norm distance as distance measure. The 256 bin histograms are normalized with their respective image size before wavelet pyramid computation. For fuzzy histogram convolution with Gaussian function is done before wavelet pyramid computation. The performance is measured using Normalised Rank Sum(NRS)[1]. NRS is defined as the ratio of sum of ranks of desired images retrieved with the given system to an ideal system. An ideal system will retrieve all the
Figure 4. Retrieval performance (avg ENRS value) for \( M = 50 \) and \( r = 60\% \)

Now in some cases all the desired images do not lie in top 50 matches so we define an Extended NRS (ENRS) as

\[
ENRS = NRS \times \frac{\text{no. of desired images retrieved}}{\text{total no. of desired images}}
\]  

We calculate the average value of ENRS for all of the above 50 sets of images using the proposed wavelet histogram matching, wavelet based fuzzy histogram and multiresolution histogram matching. From Fig.3-6 we can see that the performance of MRH technique and the proposed technique is quite comparable. Use of fuzzy histograms gives slight better performance over normal histograms. Fig.7 shows the retrieval results for an example query image using multiresolution histograms. Fig.8 shows retrieval results for same query image using wavelet based multiresolution histograms while Fig.9 shows the retrieval results with same query image using wavelet based fuzzy histograms. Fig.10-12 shows performance for different values of \( M \) for \( r = 50\% \)
Figure 9. Retrieval performance for a sample query image using wavelet based fuzzy histograms

Figure 10. Retrieval performance (avg ENRS value) for $r=50\%, M=20$

Figure 11. Retrieval performance (avg ENRS value) for $r=50\%, M=30$

Figure 12. Retrieval performance (avg ENRS value) for $r=50\%, M=40$

6. CONCLUSION

In this paper we propose a fast feature matching algorithm using wavelet based multiresolution histogram for fast image retrieval. We reduce computational cost by discarding most of the unworthy candidate images at low resolution levels. We employ wavelet pyramid structure to reuse previously computed information thereby reducing the complexity of MRH. The proposed algorithm reduces the memory overhead by 50% thus saving disc space. This algorithm can be easily combined with tree based and other algorithms for performance enhancement[2].

REFERENCES


