Recognition of Enhanced Images

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Abstract

Image enhancement such as adjusting brightness and contrast is central to improving human visualization of images’ content. Images in desired enhanced quality facilitate analysis, interpretation, classification, information exchange, indexing and retrieval. The adjustment process, guided by diverse enhancement objectives and subjective human judgment, often produces various versions of the same image. Despite the preservation of content under these operations, enhanced images are treated as new in most existing techniques via their widely different features. This leads to difficulties in recognition and retrieval of images across application domains and user interest. To allow unrestricted enhancement flexibility, accurate identification of images and their enhanced versions is therefore essential.

In this paper, we introduce a measure that theoretically guarantees the identification of all enhanced images originated from one. In our approach, images are represented by points in multidimensional intensity-based space. We show that points representing images of the same content are confined in a well-defined area that can be identified by a so-devised formula. We evaluated our technique on large sets of images from various categories, including medical, satellite, texture, color images and scanned documents. The proposed measure yields an actual recognition rate approaching 100% in all image categories, outperforming other well-known techniques by a wide margin. Our analysis at the same time can serve as a basis for determining the minimum criterion a similarity measure should satisfy. We discuss also how to apply the formula as a similarity measure in existing systems to support general image retrieval.

1. Introduction

The explosion of image availability in recent years has attracted much research addressing problems involving images [19], [9], [15]. The performance of these systems depends on the quality of input images, whether they are satellite, medical, texture, general images or scanned documents. In general, quality enhanced images help improve the quality of interpretation, analysis, classification and segmentation. They also facilitate information exchange and indexing/retrieval.

Images are normally acquired using a variety of devices such as cameras, scanners, satellites, ultrasound and X-ray machines. The quality of these initial images varies depending on the capturing devices and present environmental factors (e.g., lighting conditions). Most must undergo some enhancement operations such as brightness and contrast adjustment to improve the visual content (e.g., to correct lighting conditions at the time of capture, to highlight areas of interest) for subsequent processing.

Guided by diverse enhancement objectives and subjective human judgment, the adjustment process often produces different products from an initial image. In medical-image processing, for instance, there is no standard for enhancement settings [5], and it is left to the manipulator to bring the image to the level of acceptable quality for further processing. In some applications, several enhanced images might be needed. For example, ranges of various intensity values in satellite images need adjustments to improve contrast characteristics of different biophysical materials captured by remote sensed imagery [2]. As a result, many versions of the same image may exist.

To facilitate classification, indexing/retrieval, existing content-based techniques extract various features of images, and similarity of images is determined based on the distance between these features. Although the content of enhanced images is generally preserved under enhancement operations, these operations may produce dramatic shifts in the feature domain such that the employed measure treats them as completely different images. It is a major challenge to execute in these techniques some basic operations, such as ‘Find previous analysis associated with a given image, raw or enhanced,’ or ‘Store this image, provided that no version of it, raw or enhanced, is already stored.’
One extreme solution could be to force a standard for enhanced operations across application domains and needs: all captured images must be enhanced with a set of standardized settings. This is obviously an unrealistic approach. At the other end is a technique that enables recognition of all images enhanced from one.

This paper examines the problem of identifying images enhanced by operations including brightness adjustment, contrast enhancement and inverting (producing the negative version of the image), and attempts to propose the second solution. In our approach, images are represented by points in high dimensional space. We show that points representing enhanced images are confined in a well-defined area that can be identified by a similarity measure. The formula is derived with the help of geometric insights and is very efficient to compute. We evaluated our technique on large sets of images including medical, satellite, texture, general images and scanned documents. The recognition rate approaches 100% in all tested categories. Our approach at the same time serves as a basis to determine the minimum criterion for image retrieval. Any image-similarity measure should satisfy this criterion.

The remainder of this paper is organized as follows. Section 2 reviews some well-known works and summarizes a major difficulty in retrieval of enhanced images using existing techniques. We describe our approach in Section 3, and the measure is introduced in Section 4. Section 5 presents the results of our experimental study. We discuss how to use the measure as a similarity measure in Section 6. Finally, we have concluding remarks in Section 7.

2. Related Works

Although the need for recognizing enhanced images clearly warrants urgent attention, an extensive survey of literature revealed that little research has been devoted to address this problem. In fact, we are not aware of any such a solution. Therefore, we look into some well-known techniques in the area of analysis, classification, indexing and retrieval, in an attempt to determine their effectiveness for enhanced images.

Many approaches have been proposed for texture-based image retrieval using the multiresolution techniques such as discrete wavelet transform (DWT) [11]. Research has shown that algorithms using the DWT can achieve very good performance on texture analysis [9], [20], [17]. In [20], the DWT can obtain a much better classification rate and retrieval accuracy than other typical image decompositions such as discrete cosine transform (DCT) and spatial partitioning. Furthermore, many types of DWT-based texture features for image retrieval are compared in [17].

DCT is currently the most effective and popular technique for image and video compression. There are many approaches proposing the use of DCT features for edge description and texture analysis, e.g., [16]. Comparisons with the DWT features indicate that the proposed DCT features, such as [14], [21], [15], provide the same texture-pattern retrieval accuracy without decompressing the image data.

The Alexandria project [18] was initiated to build a digital library for map and satellite images. Designed for content-based retrieval, the relevant information in each image is encoded in the form of a multidimensional feature vector. Though representing images by feature vectors greatly facilitates user queries, indexing these vectors degrades performance when the number of dimensions is large. [10] considers discrete Fourier transform (DFT) to reduce the dimension of feature vectors, and study their retrieval performance with respect to recall and precision. It concluded that DFT compares favorably over support vector machines in a limited range suitable for browsing large image databases.

Histogram Intersection (HI) is introduced in [22] for the efficient matching model and image histograms. HI has been widely used for image recognition.

We observe that it is difficult to extend the above techniques for enhanced images. Among major obstacles are the representation of images and similarity measures on extracted features. Figure 1 highlights the difficulty of using intensity histograms to identify enhanced images. It shows an original image \( P \) (i.e., available ‘as is’ from the public archive) and enhanced ones obtained using Adobe Photoshop with various settings, including auto contrast (A), inverting (B), brightness = +50 (C), contrast = +50 (D) and contrast = -80 (E). (B or E could well be the initial image). The accompanied histograms can be seen so widely different that no histogram-based technique could be effective. Also reported are the means and the standard deviations of the images’ pixel values: \( P: (123.92, 46.20), A: (120.33, 65.34), B: (131.08, 46.20), C: (173.61, 45.63), D: (124.12, 82.95) \) and \( E: (123.98, 9.24) \). The discrepancies between the corresponding values indicate that techniques based on these (e.g., the mean as the most dominant coefficient in DCT, DFT and DWT) would not be robust in recognizing enhanced images. Our performance study was designed to evaluate these techniques for enhanced images.

There are yet numerous methods (low-level features or semantic based) that use images’ intensities or features extracted from DWT, DFT, DCT or histograms (e.g., [23], [7], [6]). The recognition effectiveness of these schemes is ultimately determined by the features extracted. We do not review those here.

3. Proposed Technique

To simplify discussion we focus on whole matching of gray-scale images. We include color images in our experi-
ments and discuss how to extend this technique to address subimage matching and robustness to translation, rotation and scaling later in the paper.

3.1. Enhancement Operations

Consider $P$, an image whose pixel intensities are $p_1, p_2, \ldots, p_n$. Let $P'(p_1', p_2', \ldots, p_n')$ be an enhanced image of $P$. The output image $P'$ can be defined as a linear point operation on the intensities of $P$ [8]:

$$p'_i = a \cdot p_i + b$$  \hspace{1cm} (1)

where $p'_i$ is the intensity level of the output point corresponding to an input point having intensity level $p_i$. If $a = 1$ and $b = 0$, we have the identity operation that merely copies $P$ to $P'$. If $a > 1$, the contrast will be increased in the output image. For $a < 1$, the contrast is reduced. If $a = 1$ and $b$ is non zero, the operation merely shifts the intensity-level values of all pixels up or down. The effect of this is to make the entire image appear darker or lighter when displayed. If $a = -1$, the image is inverted by the operation. For $a < 0$, the contrast of the inverted is changed. A series of enhancement operations is equivalent to image modifications involving both $a$ and $b$. Note that $a = 0$ is not allowed as it creates a $P'$ whose $p'_i = b$, a solid gray image regardless of the input image.

Other nonlinear point operations are possible such as nondecreasing intensity-scale transformation functions – those that have a finite positive slope everywhere [8]. In general, these functions preserve the basic appearance of an image, but do not maintain the linear-intensity relationship among pixels, thus they are not preferred in some applications. We will first consider the linear operation, which is followed by a discussion of other functions including smoothing, nonlinear transformations and quantization.

3.2. Representation of Images

An image $P$ with intensity values $p_1, p_2, \ldots, p_n$ can be represented as a point in $n$-dimensional $(n$-D) space. Let $\mu_P = \sum_{i=1}^n p_i/n$, the average of the intensity values of image $P$. The locus of points $X(x_1, x_2, \ldots, x_n)$ whose intensity average equals $\mu_P$ satisfies the equation:

$$\mu_P = \frac{x_1 + x_2 + \ldots + x_n}{n}$$

$$\Rightarrow n \cdot \mu_P = x_1 + x_2 + \ldots + x_n$$

This is a hyperplane $H_P$ passing through $P$ and whose normal is parallel to the diagonal $N$ of the space, see Figure 2(a). We now determine $b$ in Eq. 1 and interpret the geometric meanings of the new equation.

Let $M_P(m_1, m_2, \ldots, m_n) \in H_P \cap N$, then $m_1 = m_2 = \ldots = m_n = m_P$ and $\sum_{i=1}^n p_i = n m_P$. Let $P'$ be an enhanced image of $P$, and $M_{P'}$ is similarly defined for $P'$. We have

$$\sum_{i=1}^n a p_i + b = m_{P'}$$

$$\Rightarrow a \sum_{i=1}^n p_i + \frac{\sum_{i=1}^n b}{n} = m_{P'}$$

$$\Rightarrow a m_P + b = m_{P'}$$

$$\Rightarrow b = m_{P'} - a m_P$$

And from Eq. 1

$$\Rightarrow p'_i = a p_i + m_{P'} - a m_P$$

We will now determine the locus of points representing images with brightness-only adjustment, contrast-only enhancement and both.

3.2.1. Brightness Adjustment For brightness-only adjustment operations, $a = 1$. We have

$$p'_i = ap_i + m_{P'} - a m_P$$

$$\Rightarrow p'_i = p_i + m_{P'} - m_P$$

$$\Rightarrow p'_i - p_i = m_{P'} - m_P$$

Figure 1. Enhanced images and their histograms
3.2.2. Contrast Enhancement

We first consider the case $\mu_P = \mu_P$, i.e., $M_P = P$. We have

$$p'_i = a p_i + m_{P'} - a m_P$$

$$\Rightarrow p'_i = a(p_i - m_P) + m_P$$

$$\Rightarrow p'_i - m_P = a(p_i - m_P)$$

The above equation implies that vector $M_P P'$ is parallel to vector $M_P P$. Thus, $P'$ is on the line passing through $M_P$ and $P$. In Figure 2(a), contrast-enhanced enhancements of $P$, shown as $D$, $E$ and $B$, are on the line passing through points $M$ and $P$. Point $B$ is the inverted image of $P$, produced with $a = -1$. Again, this is true for any image which is contrast-enhanced from $P$, we have:

**Lemma 1** All brightness-enhanced images originated from image $P$ are on the line passing through $P$ and parallel to the diagonal of the space.

3.2.3. Enhancement Operations

For images under a series of enhancement operations, i.e., $a \neq 0$ and $b$ is arbitrary, we have

$$p'_i = a p_i + m_{P'} - a m_P$$

$$\Rightarrow p'_i = a(p_i - m_P) + m_P$$

$$\Rightarrow p'_i - m_P = a(p_i - m_P)$$

In other words, vector $M_P P'$ is linearly dependent on vector $M_P P$. Figure 2(b) shows the geometric relationship between $P$ and $P'$ ($P'$ corresponds to the auto-contrast image $A$ in Figure 1). Point $P$ and points representing enhanced versions of $P$ can be seen on the 2-D plane $PN$. We prove the following result.

**Theorem 1** Points are on the plane defined by point $P$ and the diagonal of the space iff they represent images enhanced from $P$ under the linear operation Eq. 1.

**Proof:** We need to prove that any point that lies on the plane representing an enhanced image originated from $P$, and the presentation of any enhanced image originated from $P$ is on the plane. It is evident that both conditions follow the above result, i.e., vector $M_P P'$ is linearly dependent of vector $M_P P$.

4. Identification of Enhanced Images

In the previous section, we proved that all enhanced images of $P$ are confined in a well-defined area, the 2-D plane passing through $P$ and $N$. We need to derive a formula to isolate this area. Note that $m_P = \mu_P$ and $m_{P'} = \mu_{P'}$, and let $\beta$ be the angle between $M_P P$ and $M_{P'} P'$. We rewrite the above theorem as follows. $P'$ is an enhanced image of $P$ iff the condition holds that:

$$|\cos \beta| = \frac{\sum_{i=1}^{n}(p_i - \mu_P)(p'_i - \mu_{P'})}{||M_P P|| \cdot ||M_P P'||} = 1$$

The rationale behind the above formula is clear: since $M_{P'} P'$ is parallel to $M_P P$, then $\beta = 0, \pi$; or $|\cos \beta| = 1$. The formula ensures the retrieval of all enhanced images given any image on the plane (excluding the one on the diagonal, i.e. $M$). To remove the denominator, the vectors are normalized so that their lengths equal 1.

4.1. Enhancing Real Images

The above results are valid for pixel values as a real number and without upper and lower limits. Intensities of
images’ pixels are integers ranging from 0 to 255. Thus the output of an enhancement operation has additional constraints:

\[
p'_i = \begin{cases} 
0 & [a(p_i - \mu_P) + \mu_P] < 0 \\
255 & [a(p_i - \mu_P) + \mu_P] > 255 \\
[a(p_i - \mu_P) + \mu_P] & \text{otherwise}
\end{cases}
\]

These constraints might displace certain enhanced images off the plane by a small degree. Image smoothing, resizing, quantization and enhancements under nonlinear operations could also push modified images off the plane. It is possible to determine the locus of these points with further analysis. However, the displacements are expected to be very small, and the images can be discovered with a slight modification of the formula. Let \( Q \) be an image. The similarity of \( Q \) and \( P \) is defined as:

\[
S(P, Q) = \left| \sum_{i=1}^{n} (p_i - \mu_P)(q_i - \mu_Q) \right|
\]  

(2)

The similarity score ranges from 0 to 1. When \( S = 1 \) only enhanced images on the plane are recognized. For large \( S \), other images, enhanced from \( P \) or similar, can be retrieved as well. As a similarity measure, the above formula ensures the minimal set of images (i.e., including all enhanced versions of the query image) is retrieved.

It is evident that many image-recognition measures do not have this property. From the illustrations in Figure 2, we can see that the Euclidean distance (a hypersphere centered at \( P \)) and the cosine distance measure between \( OP \) and \( OQ \) (a hypercone) do not guarantee the retrieval of this minimal set. Attempting to retrieve all possible enhanced images originated from a query by extending the distance threshold will qualify the entire data set. The same claim can be made for techniques that are not derived on the basis of this criterion. We will observe this effect via the performance of some well-known techniques in Section 5.

4.2. Image Feature Vectors for General Images

Formula 2 applies to the feature vectors that are made up of all the intensity values of the images. The scores are very reliable in classification of images. In practice, feature vectors of a much smaller size already yield excellent performance. This reduction can be achieved by sampling or by resizing the images. The reduction of an image \( P \) can be thought of as a new image \( P' \) in which the relationships between intensities are preserved. That is, let \( p'_x \) and \( p'_y \) be the two values sampled from some \( p_i \) and \( p_j \) of \( P \), respectively:

\[
p_i \leq p_j \Rightarrow p'_x \leq p'_y
\]

The established results can be applied for the reduced vectors, and Formula 2 lower-bounds the similarity scores of the initial images. Reduced effectiveness is introduced in the process, but expected to be greatly offset by the very high effectiveness of the formula.

It can be seen that the discussion so far also applies to color images. In this case, the intensity values are extracted from the luminance components of images’ pixels. The color components (i.e., chrominance) can be retained and considered in similarity matching if desired. We show in the next section that our technique is very effective for enhanced color images. Though, we did not keep and consider color components in their rankings.

One final note is Formula 2 can be computed very fast. There is no need for an indexing technique for moderate-size datasets (about 25000 in our study), although there are some available to speed up the search on very large sets.

5. Performance Study

To demonstrate the recognition effectiveness of the proposed measure, we compared it with DFT (using Fast FT), DWT, DCT and HI. These methods have been employed to extract features of medical, satellite, texture, general color images and scanned documents in a variety of application domains such as image analysis, classification, indexing and retrieval. In the implementation of all schemes, the size of the feature vectors is 16, that is, 4x4 coefficients of DFT, DWT and DCT; 16 largest bins in HI. In our technique, we implemented two methods to reduce the size of the feature vectors: 16 uniformly sampling locations (US) and the intensities of 4x4 resized images (RS).

We collected a large test set, consisting of images from various categories: medical images from [3], texture and satellite images from [1], scanned documents from [4] and general color images from a variety of sources. For each image, we used Adobe Photoshop version 6.0 to generate a number of enhanced images. Thus, we have the initial image (i.e., the one available) and six enhancements: by auto contrast, contrast by 50, contrast by -50, brightness by 50, brightness by -50 and inverting. For color images, intensity values are extracted after the images have been modified. We discarded the color components of the pixels.

Since some categories are small (e.g. about 500 texture images) and thus query results would not be statistically significant, we stored all the images in one bag and posed queries against this bag, which contains more than 25 000 images. 150 query images were executed, randomly picked from each of the categories. We are interested in search time, and the recognition performance of all schemes in each image category and enhancement type. In response to a query, the methods assign each image with a score in the range \([0,1]\), with 1 being the most similar. No indexing technique was used in the experiments.
5.1. Search Time

Table 1 compares the average sequential-search time over all queries. It can be seen that HI is significantly faster than DFT, DWT and DCT. The present approach is even faster, requiring about 80% of HI’s search time.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Search time (sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DFT</td>
<td>4.25</td>
</tr>
<tr>
<td>DWT</td>
<td>4.21</td>
</tr>
<tr>
<td>DCT</td>
<td>4.17</td>
</tr>
<tr>
<td>HI</td>
<td>1.13</td>
</tr>
<tr>
<td>US</td>
<td>0.9</td>
</tr>
<tr>
<td>RS</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Table 1. Search time

5.2. Recognition Performance

Figure 3 summarizes the recall performance of the compared techniques for each image category. The figure shows the recalls by each method in the top-ranked 10 images (a), 30 (b) and 50 (c). HI performs worse in all categories, achieving about 15%. DFT, DWT and DCT’s performance varies according to the categories. They appear to perform well for texture images, but not as well for scanned documents. It also shows that US and RS’s recall rates are comparable and approach 100% for all categories. These results indicate that enhanced images are ranked very high by US and RS.

The poor recall performances by the compared techniques imply that they rank enhanced images very low. Table 2 shows the average rank of all enhanced images of the queries (the highest average rank is \((1 + 2 + 3 + 4 + 5 + 6 + 7)/7 = 4\)). It is impressive that both implementations of the present approach are able to return most enhanced images in the top eights. None of the others come even close.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Med</th>
<th>Texture</th>
<th>Scanned</th>
<th>Sat</th>
<th>General</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>6.78</td>
<td>5.28</td>
<td>5.58</td>
<td>4.28</td>
<td>5.56</td>
</tr>
<tr>
<td>RS</td>
<td>7.71</td>
<td>5.28</td>
<td>21</td>
<td>8.42</td>
<td>4.43</td>
</tr>
<tr>
<td>DFT</td>
<td>3799.5</td>
<td>2892.2</td>
<td>1587.2</td>
<td>3297.5</td>
<td>3680.7</td>
</tr>
<tr>
<td>DWT</td>
<td>3168.7</td>
<td>2193</td>
<td>1418.7</td>
<td>2742.7</td>
<td>2919.9</td>
</tr>
<tr>
<td>DCT</td>
<td>2757.5</td>
<td>2006.5</td>
<td>1350.7</td>
<td>2496.5</td>
<td>2711.9</td>
</tr>
<tr>
<td>HI</td>
<td>5250.4</td>
<td>4909.3</td>
<td>3511.5</td>
<td>5898.4</td>
<td>3631.9</td>
</tr>
</tbody>
</table>

Table 2. Average ranks of enhanced images

A low average rank means enhanced images are not likely to be retrieved or else a very large set must be returned.

The ranking of a relevant image is a measure relative to the similarity of the others. On the other hand, the score of it provides a more objective indication of how well the technique would perform on a larger database. Figure 4 presents the average score assigned to enhanced images by the compared schemes. Again, both US and RS give very high scores to enhanced images, close to the perfect score when matched against the queries.

The recognition performances of the techniques are not the same across enhancement operations. Table 3 summarizes the performance of the techniques for each type of the enhancement operations. It can be seen that DFT, DWT and
Table 3. The average rank of images under different enhancement operations (the initial as query)

<table>
<thead>
<tr>
<th>Methods</th>
<th>contrast 50</th>
<th>contrast -50</th>
<th>bright 50</th>
<th>bright -50</th>
<th>inverting</th>
<th>auto contrast</th>
</tr>
</thead>
<tbody>
<tr>
<td>US</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>RS</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>38</td>
</tr>
<tr>
<td>DFT</td>
<td>34</td>
<td>70</td>
<td>226</td>
<td>1309</td>
<td>5410</td>
<td>16033</td>
</tr>
<tr>
<td>DWT</td>
<td>2</td>
<td>4</td>
<td>59</td>
<td>568</td>
<td>3598</td>
<td>14967</td>
</tr>
<tr>
<td>DCT</td>
<td>2</td>
<td>3</td>
<td>42</td>
<td>458</td>
<td>2887</td>
<td>14083</td>
</tr>
<tr>
<td>HI</td>
<td>73</td>
<td>470</td>
<td>2801</td>
<td>4125</td>
<td>12007</td>
<td>21812</td>
</tr>
</tbody>
</table>

DCT perform well for contrast-only enhancements, while they are not very effective for brightness adjustment and inverting. As observed in Section 2, this is attributed to the fact that the mean is the most dominant component in their measures. HI performs worst among the competitive schemes. We observe that the competitive schemes perform extremely poorly for auto-contrast enhancement, which is often a recommended enhancement operation.

Figure 5 shows some sample queries and their results (resized for display). The rows are the top-ranked images returned by each technique. We removed from the displays the query images, which always have the score of 1. It can be seen that all enhanced images compete for top spots in the proposed approach (e.g., RS scores the results of the texture query respectively: 0.999999, 0.999923, 0.999918, 0.999860, 0.999853 and 0.999307), while they scatter in the competitive methods.

6. Discussion

Clearly, any image and its enhancements should be considered the same and recognized as such in image recognition. This affirmation comes directly from the fact that enhancement operations preserve the content of processed images. We strongly believe that it should constitute a minimum requirement that any image-similarity measure should satisfy, be it for classification, indexing/retrieval or otherwise. Such a minimum criterion ensures unrestricted flexibility in enhancing images for targeted applications.

Several recent techniques such as [13], [24] and [12] can be modified to accommodate the proposed measure. Moreover, it is possible to combine their advantages and design one that supports arbitrary region matching; is robust to translation, rotation, scaling, occlusion and is efficient for large datasets of color images. We are investigating an image-retrieval procedure, as sketched below:

1. Smooth and enhance images as desired.
2. Slide windows of various sizes over the images.
3. For each window, identify landmarks (e.g. using medial axis method) and capture spatial relationships among the landmarks (e.g. with skeletal graphs).
4. Store the intensity of the landmarks along with the structure of the graphs (in compressed signatures).
5. Index the signatures (similar to [24]). The index can help quickly reduce the search space.
6. Formula 2 is used to measure similarity of images using the intensities of the landmarks.

7. Concluding Remarks

We addressed the problem of recognition of enhanced images originated from one. We showed that they can be represented by points in multidimensional intensity-based space, and they are confined in a well-defined area. We devised a measure that guarantees retrieval of enhanced images. The recognition rate approaches 100% in our experimental study on a large dataset. We suggest that this be used as a minimum criterion for any image-similarity measure.

We are evaluating this technique for other image modifications (e.g., noise reduction, low- and high-pass filtering). We are also investigating the effectiveness of other image features and similarity measures that can guarantee retrieval of the minimal set. We expect to present our results in the near future.

References

Figure 5. Top-ranked images (excluding the query)


