

Human-centered object-based image retrieval

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Abstract. A new object-based image retrieval (OBIR) scheme is introduced. The images are analyzed using the recently developed, human-based 11 colors quantization scheme and the color correlogram. Their output served as input for the image segmentation algorithm: agglomerative merging, which is extended to color images. From the resulting coarse segments, boundaries are extracted by pixel-wise classification, which are smoothed by an opening operation. The resulting features of the extracted shapes, completed the data for a <color, texture, shape>-vector. Combined with the intersection distance measure, this vector is used for OBIR, as are its components. Although shape matching solely provides good results, the complete vector outperforms its components, with up to 80% precision. Hence, an unique, excellent performing, fast, on human perception based, OBIR scheme is launched.

1 Introduction

More and more, the world wide web (www), databases, and private collections are searched for audio, video, and image material. Subsequently, the need for efficient user-friendly multimedia retrieval and indexing techniques is eminent [1]. However, where speech and handwriting recognition algorithms are generally applicable, image and video retrieval systems are only successful in a closed domain. What these techniques have in common is their computational burden and results judged as non-intuitive by its users.

In this paper, these drawbacks are tackled, for the field of content-based image retrieval (CBIR). An object-based approach on CBIR is employed: object-based image retrieval (OBIR), inspired by the findings of Schomaker, Vuurpijl, and De Leau [2], who showed that 72% of the people are interested in objects when searching images. Moreover, a human-centered approach is chosen, based on the 11 color categories used by humans in color processing, as described in Section 2. These 11 color categories are also utilized for texture analysis, as discussed in Section 2.1, and for image segmentation, done by agglomerative merging (see Section 3.1). From the resulting, coarse image segments, the shape of the object is derived using pixelwise classification (Section 3.2). Next, an opening operation is applied on the boundary in order to smooth it, as described in Section 3.3. OBIR is conducted using four query schemes (see Section 5): two of them are based on color and texture, one on the object boundaries, and one on their combination. The results are presented in Section 6 followed by a discussion in Section 7.

2 Color and Texture in 11 categories

As mentioned by Forsyth and Ponce [3]: “It is surprisingly difficult to predict what colors a human will see in a complex scene.” However, it is known that humans use 11 color categories (red, green, blue, yellow, orange, brown, pink, purple, black, white, and gray) with processing color. These 11 color categories are considered as being universal and as being optimal [4,5]. These categories should, therefore, be: (i) generic, (ii) computationally cheap, and (iii) can be expected to yield results that are intuitive for users. This triplet of advantages supports the aim to tackle the computational burden of CBIR (cf. QBIC uses a scheme with 4096 colors [6]) and to provide intuitive results for the users [7]. Therefore, we adopted the 11 color quantization scheme [8]: a unique color space segmentation, based on data gathered through experiments in which subjects categorized colors into the 11 color categories. So, the color distribution of images is characterized by a color vector with 11 color values.

Next to color, texture is an important feature for the human visual system [9]. Texture analysis can be done based on intensity differences, but nevertheless, color is important in texture recognition of colorful image material. With respect to color representation, Fujii, Sugo, and Ando [9] stated that “considering the effective computational strategy in our visual system, it is quite possible that not all the information carried out by the high-dimensional sensory representation is preserved for rapid judgments of natural textures.” Taken this into account, the 11 color category quantization scheme should perfectly fit the job, and is, therefore, applied for colorful texture analysis.

For the analysis of texture, various methods are available, such as: statistical methods (e.g., co-occurrence matrices and autocorrelation features), geometrical methods (e.g., Voronoi tessellation features and structural methods), model based methods (e.g., random field models and fractals), and signal processing methods (e.g., spatial domain filters, Fourier domain filtering, Gabor models, and Wavelet models). Originally, they are developed for gray-value images but some of them are recently adapted to fit texture analysis on color images.

2.1 The color correlogram

For the current research, one of the most intuitive texture analysis methods is applied: the color correlogram, as suggested by Huang, Kumar, Mitra, Zhu, and Zabih [10], which is constructed from an image by estimating the pairwise statistics of pixel color. In order to (i) provide perceptual intuitive results and (ii) tackle the computational burden, the 11 color scheme for quantization of color is chosen.

The color correlogram $C_{\bar{d}}(i, j)$ counts the co-occurrence of pixels with colors i and j at a given distance \bar{d} . The distance \bar{d} is defined in polar coordinates (d, α) , with discrete length and orientation. In practice, α takes the values $0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ,$ and 315° . The color correlogram $C_{\bar{d}}(i, j)$ can now be defined as follows:

$$C_{i,j}^{\bar{d}}(I) = \Pr(I(p_1) = i \wedge I(p_2) = j \mid |p_1 - p_2| = \bar{d}), \quad (1)$$

where \Pr is probability and p_1 and p_2 are positions in the color image I . Let N be the number of colors in the image, then the dimension of the color correlogram $C_{\bar{d}}(i, j)$ will be $N \times N$, which is in our scheme 11×11 . This algorithm yields a symmetric matrix. Hence, only angles up to 180° need to be considered. One direction insensitive color correlogram can be defined for each distance (d) by averaging the four color correlograms of the different angles (i.e., $0^\circ, 45^\circ, 90^\circ,$ and 135°).

From the color correlogram, a large number of textural features can be derived, such as: energy, entropy, correlation, inverse difference moment, inertia, Haralick's correlation, cluster shade, and cluster prominence, which characterize the content of the image. Based on previous research [11], the combination of entropy, inverse difference moment, cluster prominence, and Haralick's correlation, with distance $d = 1$ is used, resulting in a vector of four texture features.

3 Shape extraction

The shape extraction phase is divided in three stages: (i) coarse image segmentation, (ii) pixelwise classification, and (iii) smoothing. The coarse image segmentation uses only texture information to segment the image in texture regions. In the pixelwise classification phase, only color information is used because the regions are too small for our texture descriptor to be informative. The complete process of shape extraction is illustrated in Figure 1.

3.1 Segmentation by agglomerative merging

Segmentation is applied by agglomerative merging, as described by Ojala and Pietikäinen [12]. Their algorithm is a gray-scale image algorithm but is extended to color images, using a color texture descriptor. The algorithm is applied using the color correlogram as texture descriptor based on the 11 color quantization scheme.

At the initial state of the agglomerative merging algorithm, the images are divided in sub blocks of size 16×16 pixels. At each stage of the merging phase, the pair of blocks with the lowest merger importance (MI) is merged. This merger importance is

defined by the similarity measure L_1 [10]. For two images I and I' , the L_1 distance measure is defined as follows:

$$L_1 = |I - I'| = \sum_{i,j=0}^{m-1} |C_{i,j}^{\bar{d}}(I) - C_{i,j}^{\bar{d}}(I')|, \quad (2)$$

where m is the number of bins used and $C_{i,j}^{\bar{d}}(I)$ is the color correlogram of image I (see Equation 1), and \bar{d} is set to 1 (see Section 2.1). The closer L_1 is to zero, the more similar the texture regions are. When two regions are merged, the MI -values between this region and all adjacent regions are computed. The agglomerative merging phase continues until the experimentally determined stopping criterion (Y), given in Equation 3 is met:

$$MI_{stop} = \frac{MI_{cur}}{MI_{max}} < Y, \quad (3)$$

where MI_{cur} is the merger importance for the current best merge, MI_{max} is the largest merger importance of all preceding merges. For the current dataset, Y is determined to be 0.700.

When the coarse segmentation phase is complete, the center segment of the image is selected to be the object of interest for OBIR.

3.2 Pixelwise classification based on the 11 colors

After the center object is identified in the coarse segmentation phase, pixelwise classification [12] is applied to improve localization of the boundaries of the object. In pixelwise classification, each pixel on the boundary of the center object is examined. A disk with radius r is placed over the pixel and the 11 color histogram is calculated for this disk and all adjacent segments. Next, the distance between the disk and the adjacent segments is calculated, using the intersection distance measure [8] based on the 11 color histogram. The pixel is relabeled if the label of the nearest segment is different from the current label of the pixel. This process is repeated as long as there are pixels that are relabeled.

The radius r of the disk used determines how smooth the resulting boundaries are: a small radius will produce ragged regions, a larger radius will produce smoother boundaries but may fail in locating the boundaries accurately. In order to tackle these problems we used a two-step approach: in the first iterations, a relatively small radius of 5 is used, in order to locate the boundaries correctly, secondly a radius of 11 is used to produce more stable segments.

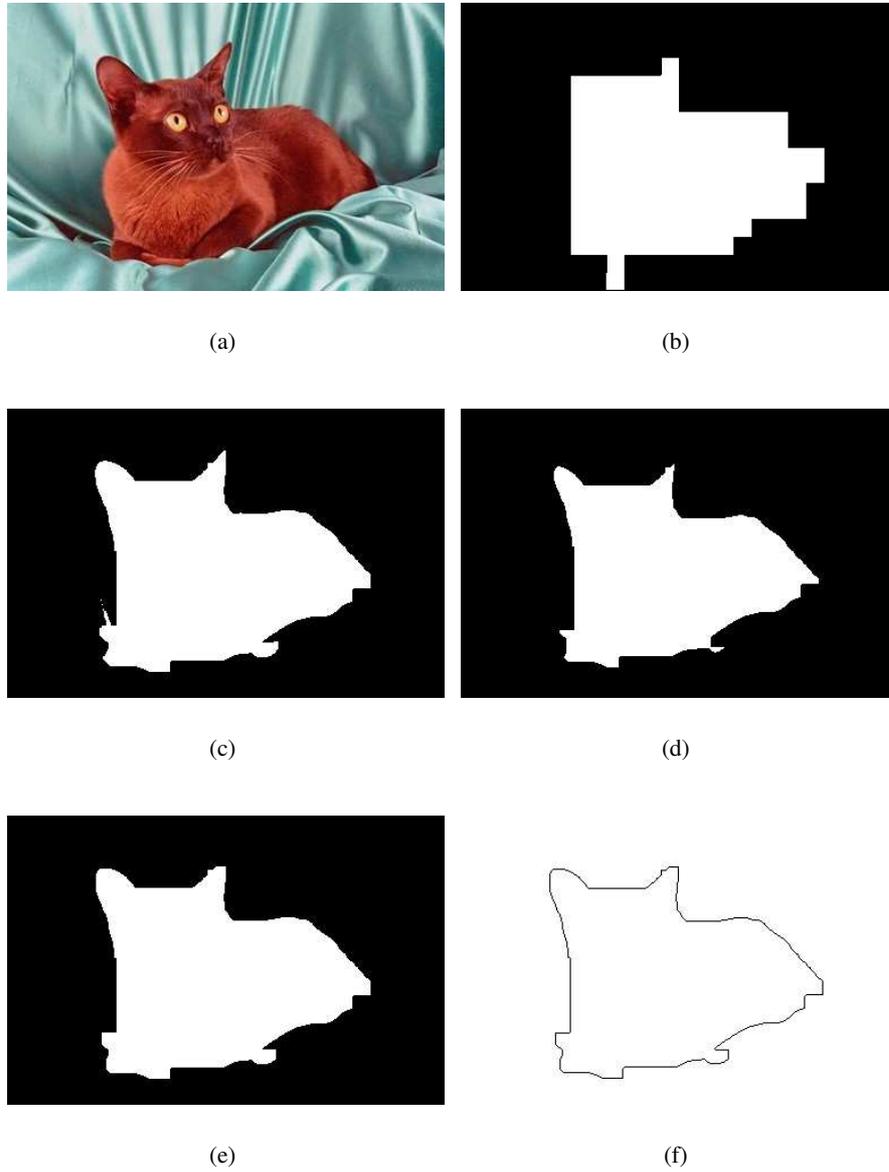


Fig. 1. (a) The original image (b) The coarse segmentation (c) The object after pixelwise classification (d) The object after erosion (e) The object after dilation (f) The final shape.

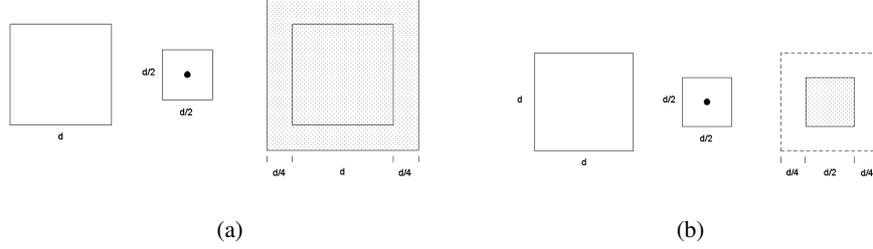


Fig. 2. The process of erosion illustrated. The left figure is the original shape A . The square in the middle is the erosion marker B (dot is the center). The middle of the marker runs over the boundary of A . The result of erosion of A by B ($A \ominus B$) is given by the solid shape on the right, in which the outer (dotted) square projects the original object A .

3.3 Smoothing

Although the pixelwise classification phase produces correct object boundaries, the shapes are smoothed to optimize for the shape matching phase. Smoothing is done using two fundamental operations: dilation and erosion, see also Figure 2.

Given two sets A and B in \mathbb{Z}^2 , the dilation of A by B is defined as:

$$A \oplus B = \{x \mid (B)_x \cap A \neq \emptyset\}, \quad (4)$$

where $(B)_x$ denotes the translation of B by $x = (x_1, x_2)$ defined as:

$$(B)_x = \{c \mid c = b + x, \text{ for some } b \in B\} \quad (5)$$

Thus, $A \oplus B$ expands A if the origin is contained in B , as is usually the case. The latter process is visualized in Figure 2a.

The erosion of A by B , denoted $A \ominus B$, is the set of all x such that B translated by x , is completely contained in A , defined as

$$A \ominus B = \{x \mid (B)_x \subseteq A\} \quad (6)$$

Thus, $A \ominus B$ decreases A . Figure 2b visualizes this process.

The smoothing is done by an opening operation; i.e., an erosion followed by a dilation using the same structuring element for both operations. The latter was done with a square marker (B) of size 5×5 pixels.

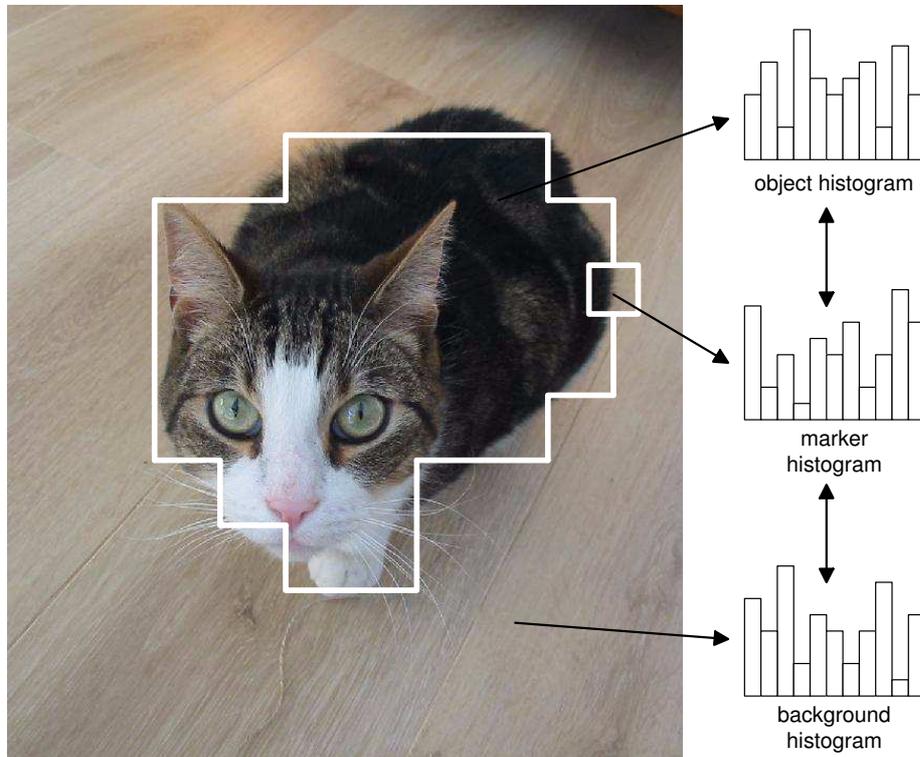


Fig. 3. The process of pixelwise classification illustrated. A pixel at the boundary is selected and a marker is placed over it. Next, the color histogram over this marker is calculated as well as the histograms of the center segment and the background. The histogram over the marker is compared to the other histograms and the pixel is assigned to the area with the most similar histogram (of the background or the object).

4 Shape matching

Shape matching has been approached in various ways. A few of the frequently applied techniques are: tree pruning, the generalized Hough transform, geometric hashing, the alignment method, various statistics, deformable templates, relaxation labeling, Fourier and wavelet transforms, curvature scale space, and classifiers such as neural networks [13].

Recently, Andreou and Sgouros [13] discussed their: “turning function difference”, as a part of their G Computer Vision library. It promises to be an efficient and effective shape matching method. However, a similar approach was launched five years before by Schomaker et al. [2]. In the current research, the latter, original approach has been adapted. This “outline pattern recognition”, as the authors call it, is based on three feature vectors containing: (i) x and y coordinates, normalized using the center of gravity of the shape and the standard deviation of all radii, (ii) the running angle (θ) along

the edge of the segment $(\cos(\theta), \sin(\theta))$, which contains more information on the local changes of direction, and (iii) the histogram of angles in the shape: the probability distribution $p(\theta)$ [2].

The algorithm was proven to be translation, scale, and rotation invariant. Based on this algorithm, the outline-based image retrieval system Vind(X)⁶ was developed and has been used successfully since then. Vind(X) relies on outline-outline matching: the user draws an outline, which is the query. This outline is matched against the outlines of images present in its database. Subsequently, the images containing the best matching outlines are retrieved and shown to the user.

The Vind(X) system provides excellent retrieval results. However, in order to make its techniques generally applicable, automatic shape extraction techniques had to be developed. Moreover, these techniques had to be computationally cheap in order to preserve (as much as possible) its fast retrieval. The latter was already achieved by the techniques as described in the previous sections. In combination with the matching algorithm of Vind(X), unsupervised OBIR was applied.

5 Method

In Sections 2 and 3, color, texture, and shape features are defined. They are combined and used in four distinct query schemes for object matching, using four vectors:

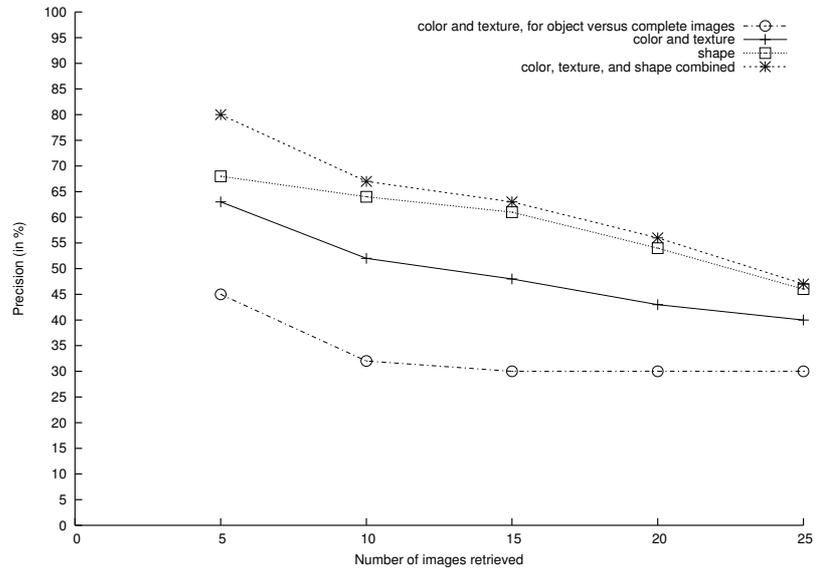
1. color and texture, for object versus complete images
2. color and texture
3. shape
4. color, texture, and shape combined

Feature-based and shape-based image retrieval was employed by two separate retrieval engines, connected to the same database, both using the intersection distance measure for ranking their results. For both engines, the number of retrieved images (n) could be chosen by the user. All query schemes performed an object - object comparison, except scheme 1 for which object features are matched with the features of the complete images in the database. For query scheme 4, for each image its ranks on both engines are summed and divided by two.

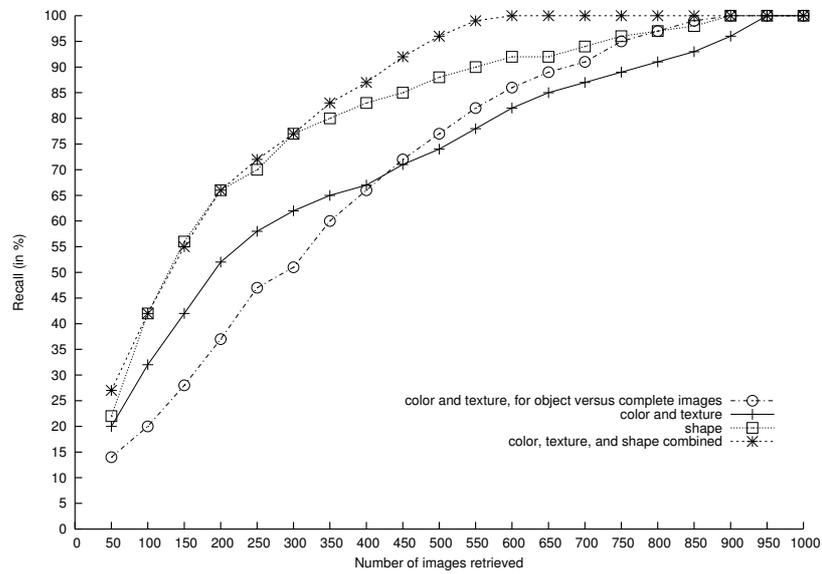
The data consisted of 1000 images from the Corel image database, a reference database for CBIR applications. Since we are interested in objects, the six categories chosen represented objects: cats, leaves, revolvers, motorbikes, pyramids, and dinosaurs.

Adapted from the field of Information Retrieval, the performance of CBIR systems can be determined by the measures recall and precision. Recall signifies the percentage of relevant images retrieved from the database in response to the query. Precision is the proportion of retrieved images that is relevant to the query.

⁶ <http://kepler.ai.ru.nl/vindx/> [Last accessed on December 21, 2005]



(a)



(b)

Fig.4. Average precision (a) and recall (b) of retrieval, with global and local color&texture features, outline of extracted objects from images, and their combination.

6 Retrieval results

Recall and precision are calculated for each of the four different query schemes, as defined in Section 5, using a variable number of images retrieved. The precision of the retrieval results for the four schemes are plotted in Figure 4(a), for 5–25 images retrieved. The recall of the retrieval results for the four schemes are plotted in Figure 4(b), for the complete dataset.

All four schemes performed good; see Figure 4(a) and 4(b). However, note that with the combined approach, four of the top five images are relevant; i.e., an average Precision of 80% was achieved. Moreover, the recall achieved with the combined approach converges much faster to 100% than with one of the other approaches.

7 Discussion

The rationale of the CBIR approach presented in this paper is that it is human centered. This is founded on two principles: (i) CBIR should be object-based and (ii) it should utilize the 11 color categories, as used by humans in color processing [8]. Both principles contribute to efficient CBIR, providing intuitive results for users. It was shown that the 11 color categories work good for describing color distributions, for the extraction of texture descriptors [11], and for object segmentation [14], as illustrated by the recall and precision of the retrieval results.

The success of matching the 2D shapes of segmented objects with each other striking. This can, at least partly, be explained by the fact that “photographers generate a limited number of ‘canonical views’ on objects, according to perceptual and artistic rules. [2]” Moreover, even in the most recent research still (computationally expensive gray-scale techniques are applied [15]). In contrast, we are able to extract shapes from colorful images. This very important, since most of the image material available on the www and other databases is colorful.

In contrast with the reality on the www, the images in our database all contain images of objects against a rather uniform background, as illustrated in Figure 5 in Appendix 7. With our database a first step is made toward processing real world images, where in comparable, recent work of Gevers and Stokman [16], object images are used that lack any background at all.

Despite the success of the current approach on real world images, it also knows some drawbacks. First, it should be noted that the number of categories and its members were limited and follow-up research should be conducted with a larger database, incorporating a large number of categories. Second, in further developing the engine, the segmentation parameter should be set dynamically; i.e., setting the parameter to a minimum value and resetting it dynamically during the merging phase, based on the texture differences between the remaining blocks. This would tackle the current dependency on a good pre-defined parameter setting. Third, the ultimate goal would be to identify all objects in an image, instead of one such as is currently the case. Fourth, the complete image should be searched for objects, instead of merely its center. Fifth, we expect that the use of artificial classifiers can improve the results, compared to the uses of a simple distance measure, such as the intersection distance. Currently, we are

working on these five topics. When this work is finished, the resulting CBIR engine can be applied on real-world images instead of only on object-classes.

In this paper, a highly efficient scheme for the extraction of color, texture, and shape features is introduced. Combined with the intersection distance measure, it formed the basis of a unique, excellent performing, fast object-based CBIR (OBIR) engine, which provides results intuitive for its users.

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Appendix

(a)



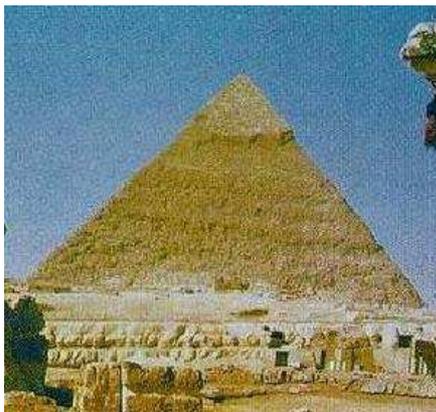
(b)



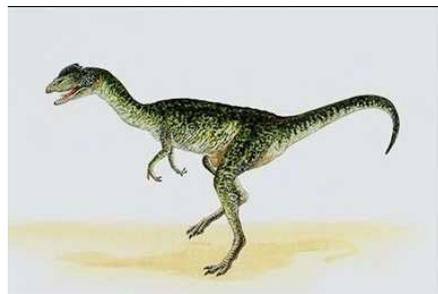
(c)



(d)



(e)



(f)

Fig. 5. Sample images from the database used.