Content-Based Sub-Image Retrieval with Relevance Feedback

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Abstract

The typical content-based image retrieval problem is to find images within a database that are similar to a given query image. This paper presents a solution to a different problem, namely that of content based sub-image retrieval, i.e., finding images from a database that contains another image. Note that this is different from finding a region in a (segmented) image that is similar to another image region given as a query. We present a technique for CBsIR that explores relevance feedback, i.e., the user’s input on intermediary results, in order to improve retrieval efficiency. Upon modeling images as a set of overlapping and recursive tiles, we use a tile re-weighting scheme that assigns penalties to each tile of the database images and updates the tile penalties for all relevant images retrieved at each iteration using both the relevant and irrelevant images identified by the user. Each tile is modelled by means of its color content using a compact but very efficient method which can, indirectly, capture some notion of texture as well, despite the fact that only color information is maintained. Performance evaluation on a largely heterogeneous dataset of over 10,000 images shows that the system can achieve a stable average recall value of 70% within the top 20 retrieved (and presented) images after only 5 iterations, with each such iteration taking about 2 seconds on an off-the-shelf desktop computer.

1 Introduction

Most of the content-based image retrieval (CBIR) systems perform retrieval based on a full image comparison, i.e., given a query image the system returns overall similar images. This is not useful if users are also interested in images from the database that contain an image (perhaps an object) similar to a query image. We call this searching process Content-Based sub-Image Retrieval (CBsIR), and it is defined as follows [18]: given an image query $Q$ and an image database $S$, retrieve from $S$ those images $Q'$ which contain $Q$ according to some notion of similarity. To illustrate this consider Figure 1 which displays an example query image and its relevant answer set. Figures 2 shows the images
Figure 1: A sample query (sub)image and its relevant answer set.

Figure 2: Rank of the relevant images obtained after the first iteration (no feedback given).

of such an answer set, and their respective ranks, retrieved within the top 20 matches after CBsIR is performed.\footnote{Incidentally, this is an example of an actual result obtained using our prototype CBsIR system, available at \url{http://db.cs.ualberta.ca/mn/CBsIR.html}} Note that the other 17 images returned are considered non-relevant to the query. Now assume that the user is given the opportunity to mark those 3 images as relevant and all other 17 as irrelevant, i.e., the user is allowed to provide relevance feedback. Figure 3 shows the relevant images retrieved (along with their rank) after taking such feedback into account. Note that all images previously obtained were ranked higher and also new images were found and ranked high as well.

The sub-image retrieval problem we consider is similar to region-based image retrieval (RBIR), e.g. \cite{1,9}, since the goal may also be to retrieve images at object-level. However, there is a fundamental difference between these two. The CBsIR problem is to search for an image, given as a whole, which is contained within another image, whereas in RBIR one is searching for a region, possibly the result of some image segmentation. The former is more intuitive since users can provide a query image as in traditional CBIR, and unlike the latter, it does not rely on any type of segmentation preprocessing. Unfortunately, automatic image segmentation algorithms usually lead to inaccurate segmentation of the image when trying to achieve homogeneous visual properties. Sometimes the ob-
tained regions are only parts of a real object and should be combined with some neighbor regions so as to represent a meaningful object. Thus, complex distance functions are generally used to compare segmented images at query time. Also, the number and size of regions per image are variable and a precise representation of the obtained regions may be storage-wise expensive. Furthermore, since region-based queries are usually performed after the image segmentation and region description steps, it clearly puts some restriction on the user’s expression of his/her information need depending on how good the segmentation results match the semantics of images, even though the user can explicitly select any detected region as query region. In those image retrieval systems where images are heterogeneous, rich in texture, very irregular and variable in contents, accurate regions are hard to obtain, making RBIR likely to perform poorly.

The main contribution of this paper is to realize CBsIR by employing relevance feedback, in order to capture the user’s intentions at query time. As we discuss in the next section, relevance feedback is an interactive learning technique which has already been demonstrated to boost performance in CBIR and RBIR systems. Despite the great potential shown by relevance feedback, to the best of our knowledge there is no published research that uses it in the context of CBsIR, thus positioning our work as unique in this domain.

The remainder of this paper is organized as follows. In the next section we discuss some related work. We also summarize the BIC method [19] for CBIR and how we adopt it for the CBsIR techniques system we propose. (As we shall discuss BIC is used as a building block when modeling images within our proposed approach.) Our retrieval strategy uses query refinement as well as the incorporation of user’s judgement, via relevance feedback, into the image similarity measure. This forms the core contribution of this paper and is detailed in Section 3. In Section 4 we present and discuss experimental results, which support our claim of improved retrieval effectiveness. Finally, Section 5 concludes the paper and offers directions for future work.
2 Related Work

In this section we initially survey some of the work done using relevance feedback (also referred to as “learning”) in the context of CBIR and then in the context of RBIR. For the sake of completeness we also briefly mention some research proposed for single-pass, i.e., not considering relevance feedback, CBsIR. Finally, we also review the BIC technique for image representation since it will be used as an important building block within our proposed approach.

2.1 Relevance Feedback within Traditional CBIR

The key issue in relevance feedback is how to use positive and negative examples to refine the query and/or to adjust the similarity measure. Early relevance feedback schemes for CBIR were adopted from feedback schemes developed for classical textual document retrieval. These schemes fall into two categories: query point movement (query refinement) and re-weighting (similarity measure refinement), both based on the well-known vector model.

The query point movement methods aim at improving the estimate of the “ideal query point” by moving it towards positive example points and away from the negative example points in the query space. One frequently used technique to iteratively update the query is the Rocchio’s formula [13]. It is used in the MARS system [16], replacing the document vector by visual feature vectors. Another approach is to update query space by selecting feature models. The best way for effective retrieval is argued to be using a “society” of feature models determined by a learning scheme since each feature model is supposed to represent one aspect of the image content more accurately than others.

Re-weighting methods enhance the importance of a feature’s dimensions, helping to retrieve relevant images while also reducing the importance of the dimensions that hinder the process. This is achieved by updating the weights of feature vectors in the distance metric. The refinement of the re-weighting method in the MARS system is called the standard deviation method.

Recent work has proposed more computationally robust methods that perform global feature optimization. The MindReader retrieval system [5] formulates a minimization problem on the parameter estimating process. Using a distance function that is not necessarily aligned with the coordinate axis, the MindReader system allows correlations between attributes in addition for different weights on each component. A further improvement over the MindReader approach [14] uses a unified framework to achieve the optimal query estimation and weighting functions. By minimizing the total distances of the positive examples from the revised query, the weighted average and a whitening transform in the feature space are found to be the optimal solutions. However, this algorithm does not use the negative examples to update the query and image similarity measure; and initially the user needs to input the critical data of training vectors and the relevance matrix into the system.

Tasks that can be improved as a result of experience can be considered as a machine-learning task. Therefore, relevance feedback can be considered as a
learning method—the system learns from the examples provided as feedback by a user, i.e., his/her experience, to refine the retrieval results. The aforementioned query-movement method represented by the Rocchio’s formula and re-weighting method are both simple learning methods. However, as users are usually reluctant to provide a large number of feedback examples, i.e., the number of training samples is very small. Furthermore, the number of feature dimensions in CBIR systems is also usually high. Thus, learning from small training samples in a very high dimension feature space makes many learning methods, such as decision tree learning and artificial neural networks, unsuitable for CBIR.

There are several key issues in addressing relevance feedback in CBIR as a small sample learning problem. First, how to quickly learn from small sets of feedback samples to improve the retrieval accuracy effectively; second, how to accumulate the knowledge learned from the feedback; and third, how to integrate low-level visual and high-level semantic features in the query. Most of the research in literature has focused on the first issue. In that respect Bayesian learning has been explored and has been shown advantageous compared with other learning methods, e.g., [21]. Active learning methods have been used to actively select samples which maximize the information gain, or minimize entropy/uncertainty in decision-making. These methods enable fast convergence of the retrieval result which in turn increases user satisfaction. Chen et al [2] use Monte carlo sampling to search for the set of samples that will minimize the expected number of future iterations. Tong and Chang [20] propose the use of SVM active learning algorithm to select the sample which maximizes the reduction in the size of the version space in which the class boundary lies. Without knowing apriori the class of a candidate, the best search is to halve the search space each time. In their work, the points near the SVM boundary are used to approximate the most-informative points; and the most-positive images are chosen as the ones farthest from the boundary on the positive side in the feature space.

2.2 Relevance Feedback within RBIR

Relevance feedback has been introduced in RBIR systems for a performance improvement as it does for the image retrieval systems using global representations.

In [6], the authors introduce several learning algorithms using the adjusted global image representation to RBIR. First, the query point movement technique is considered by assembling all the segmented regions of positive examples together and resizing the regions to emphasize the latest positive examples in order to form a composite image as the new query. Second, the application of support vector machine (SVM) [20] in relevance feedback for RBIR is discussed. Both the one class SVM as a class distribution estimator and two classes SVM as a classifier are investigated. Third, a region re-weighting algorithm is proposed corresponding to feature re-weighting. It assumes that important regions should appear more times in the positive images and fewer times in all the images of the database. For each region, measures of region frequency RF and inverse
image frequency IIF (analogous to the TF and IDF in text retrieval [22]) are introduced for the region importance. Thus the region importance is defined as its region frequency RF weighted by the inverse image frequency IIF, and normalized over all regions in an image. Also, the feedback judgement is memorized for future use by calculating the cumulate region importance. However, this algorithm only consider positive examples while ignoring the effect of the negative examples in each iteration of the retrieval results. Nevertheless, experimental results on a general-purpose image database demonstrate the effectiveness of those proposed learning methods in RBIR.

2.3 CBsIR without Relevance Feedback

The paper by Leung and Ng [8] investigates the idea of either enlarging the query sub-image to match the size of an image block obtained by the four-level multiscale representation of the database images, or conversely contracting the image blocks of the database images so that they become as small as the query sub-image. The paper presents an analytical cost model and focuses on avoiding I/O overhead during query processing time. To find a good strategy to search multiple resolutions, four techniques are investigated: the branch-and-bound algorithm, Pure Vertical (PV), Pure Horizontal (PH) and Horizontal-and-Vertical (HV). The HV strategy is argued to be the best considering efficiency. However, the authors do not report clear conclusions regarding the effectiveness (e.g., Precision and/or Recall) of their approach.

The authors of [18] consider global feature extraction to capture the spatial information within image regions. The average color and the covariance matrix of the color channels in L*a*b color space are used to represent the color distribution. They apply a three level non-recursive hierarchical partition to achieve multiscale representation of database images by overlapping regions within them. Aiming at reducing the index size of these global features, a compact abstraction for the global features of a region is introduced. As well, a new distance measure between such abstractions is introduced for efficiently searching through the tiles from the multi-scale partition strategy. This distance is called **inter hierarchical distance** (IHD) since it is taken between feature vectors of different hierarchical levels of the image partition. The IHD index is a two dimensional vector which consumes small storage space. The search strategy is a simple linear scan of the index file, which assesses the similarity between the query image and a particular database image as well as all its sub-regions using their IHD vectors. Finally, the minimum distance found is used to rank this database image.

In [11] a new method called HTM (Hierarchical Tree Matching) for the CB-sIR problem was proposed. It has three main components: (1) a tree structure that models a hierarchical partition of images into tiles using color features, (2) an index sequence to represent the tree structure (allowing fast access during the search phase), and (3) a search strategy based on the tree structures of both database images and the query image. Since the tree structure presented in [11] is re-used in our work, we detail it in the following.
To model an image, a grid is laid on it yielding a hierarchical partition and tiles. Although granularity could be arbitrary, we have obtained good results using a $4 \times 4$ grid resulting in a three-level multiscale representation of the image (similarly to what was done in [8] and [18]). The hierarchical partition of an image and its resulting tree structure are illustrated in Figure 4. There are three levels in the hierarchical structure. The highest level is the image itself. For the second level the image is decomposed into $3 \times 3$ rectangles with each side having half the length of the whole image, yielding 9 overlapping tiles. The lowest level consists of $4 \times 9 = 36$ rectangles, since each tile of the second level is partitioned into 4 non-overlapping sub-tiles. Note that, to exclude redundancy in the CBsIR system, only the indices of the $4 \times 4 = 16$ unique tiles in the lowest level are stored with a small structure for relationship information. This tiling scheme is obviously not unique and as long as a well-formed hierarchy of tiles is used to model the image the technique we proposed can still be applied after corresponding adjustments. The average color of the image tiles in the RGB color space is associated to the nodes in the tree structures for images. Thus, every database image is represented as a series of tiles, each of which is mapped to a subtree of the tree modeling the image.

An index sequence representing the predefined parent-child relationship (given by the predefined order of sequence in the index) for the tree structure is stored on secondary storage and used for fast retrieval. Details about the index sequence structure can be found in elsewhere [11]; in short, it resembles a priority tree where the relative order among the tree nodes reflect the relative order of the entries and which can be efficiently mapped onto an array structure. Such an structure allows one to efficiently traverse the necessary indices for computing (sub)image similarity. The searching process is accomplished by “floating” the tree structure of the query image over the full tree structure of the candidate database image, shrinking the query’s tree structure so that it is comparable with the candidate database image’s trees at each level of the hierarchical structure. The minimum distance from tree comparisons at all hierarchical levels, indicating the best matching tile from a database image, is used as the distance between the database image and the query. Differently from [18], the HTM search strategy considers local information of images’ tiles represented by leaf nodes in the subtree structures. The average of distance values among the corresponding leaf nodes is taken for the distance between the tree structures of query image and a certain tile of the database image at any hierarchical level.

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Even though different datasets were used, experiments detailed in [11] strongly suggest that the proposed approach yields better retrieval accuracy compared to [18], at the cost of small storage overhead.

2.4 The BIC-based Image Abstraction

An straightforward way to model images is to use its average color. This is obviously not effective in any non-trivial situation. Another simple, and in many situations cost-effective means is to use a global color histogram (GCH) (c.f., [10]). A common critique to GCHs is that it is unable to capture any notion of spatial distribution. To address this several other approaches have been proposed\(^3\), but they add complexity as a trade-off in order to gain effectiveness. Nevertheless, the use of color only, without any notion of spatial distribution, may be effective, if one is able to capture other features of the images, e.g., texture. That is exactly the advantage of the BIC technique proposed in [19] and which we re-use within our proposal.

The image analysis algorithm of BIC classifies pixels as either border, when its color is the same as its neighbors, or otherwise as interior, and two normalized histograms are computed considering only the border pixels and the interior pixels respectively. That is, for each color two histogram bins exist: one in the border pixel histogram and one in the interior pixel histogram. This allows a more informed color distribution abstraction and captures, implicitly, a notion of texture.

To illustrate the idea consider two images, one composed of two equally sized solid color blocks of different colors, say C1 and C2, and another one where half of pixels of color have color C1 and are randomly distributed. Likewise the other half of pixels have color C2 and are also randomly distributed. Clearly the BIC histograms of those images are quite different, one will have almost only interior pixels and the other will have almost only border pixels. This will yield a low similarity measure, which is indeed the case. Note that the global color histogram, a standard CBIR technique, for both images would be identical, misleading one to think the images were very similar. Note that the difference in the histogram suggests a very different texture in the images, which, on top of the possible color differences, enhances the capability of distinguishing among images even further.

Figure 5\(^4\) shows two examples of images analyzed by border and interior pixels, where the notion of capturing texture can be clearly seen. The original images are at the left column. The resulting binary images showing border pixels in black and interior pixels in white are at the middle column. The images showing border pixels in the corresponding original colors and interior pixel in white are at the right column.

For histogram comparison within BIC, the \(d\text{Log}\) distance function is used to diminish the effect that a large value in a single histogram bin dominates the

\(^3\)A comprehensive survey thereof is beyond the scope of this paper.

\(^4\) C.f. \url{http://db.cs.ualberta.ca/smn/BIC/bic-sample.html}
distance between histograms, no matter the relative importance of this single value \[10\] \[12\]. The basic motivation behind this is based on the observation that classical techniques based on global color histograms treat all colors equally, despite of their relative concentration. However, the perception of stimulus, color in images in particular, is believed to follow a “sigmoidal” curve \[12\]. The more relative increment in a stimulus is perceived more clearly when the intensity of the stimulus is smaller than when it is larger. For instance, a change from 10% to 20% of a color is perceived more clearly than a change from 85% to 95%. Indeed, it has been a well observed phenomena regarding many other phenomena involving how sensitive one is (including animals) to different stimuli \[3\]. Thus, the distance function is defined as:

\[
d\text{Log}(a, b) = \sum_{i=0}^{M} |f(a[i]) - f(b[i])|
\]

where

\[
f(x) = \begin{cases} 
0 & \text{if } x = 0 \\
1 & \text{if } 0 < x \leq 1 \\
\lceil \log_2 x \rceil + 1 & \text{otherwise}
\end{cases}
\]

and \(a[i]\) and \(b[i]\) represent the \(i^{th}\) bin of the \(M\) color histograms \(a\) and \(b\) respectively. Note that if we normalize the histograms bins in the \([0, 255]\) range of integer values, instead of usual \([0, 1]\) continuous range, the \(f(x)\) function will return integers in the range \([0, 9]\), requiring only 4 bits of storage per histogram bin. This allows substantial reduction in storage, and yet a reasonably fine discretization of the bins.

The BIC approach was shown in \[19\] to outperform several other CBIR approaches and, as such, we adopt it in our CBSIR proposal to extract and compare the visual feature of each tile with the goal of improving the retrieval accuracy.
3 Relevance Feedback for CBsIR

Despite the great potential of relevance feedback shown in CBIR systems using global representations and in RBIR systems, to the best of our knowledge there is no research that uses it within CBsIR systems. In this section we present our solution for CBsIR by using relevance feedback to learn the user’s intention. Our relevance feedback approach has three main components: (1) a tile re-weighting scheme that assigns penalties to each tile of database images and updates those tile penalties for all relevant images retrieved at each iteration using both the relevant (positive) and irrelevant (negative) images identified by the user; (2) a query refinement strategy that is based on the tile re-weighting scheme to approach the most informative query according to the user’s intention; (3) an image similarity measure that refines the final ranking of images using the user’s feedback information. Each of these components is explained in detail in the following subsections.

3.1 Tile Re-Weighting Scheme

Researches in RBIR [7, 6] have proposed region re-weighting schemes for relevance feedback. In this research, we design our tile re-weighting scheme that specializes the technique presented in [7] to accommodate our tile-oriented (not region-oriented) HTM approach for CBsIR. It should be emphasized that instead of considering all the images in the database to compute the parameters for region weight [6] (which is computationally expensive), our tile re-weighting scheme uses only the positive and negative examples identified by the user to update the tile penalty of the positive images only, which is much more efficient. Moreover, the region re-weighting scheme in [7] uses a predefined similarity threshold to determine whether the region and the image is similar or not, otherwise the comparison of region pairs would become too expensive since images might consist of different and large number of regions. This threshold is sensitive and subject to change for different kinds of image datasets. Thus, how to obtain the right threshold is yet another challenge for the relevance feedback method in RBIR. However, our RF method for the CBsIR problem does not need any threshold because the number of obtained tiles is the same (and small) for each database image and there exists implicit relationship between the tiles, which makes it easier to compare them.

In our system, the user provides feedback information by identifying positive and negative examples from the retrieved images. The basic assumption is that important tiles should appear more often in positive images than unimportant tiles, e.g., “background tiles” should yield to “theme tiles” in positive images. On the other hand, important tiles should appear less often in negative images than unimportant tiles. Following the principle of “more similar means better matched thus less penalty”, we assign a penalty to every tile that represents the database image for the matching process. User’s feedback information is used to estimate the “tile penalties” for all positive images, which also refines the final ranking of images. During the feedback iterations, the user does not need
to specify which tile of a certain positive image is similar to the query, which would only make the problem only simpler to solve at an additional cost to the user.

Next, we introduce some definitions used to determine the tile penalty and formalize the overall relevance feedback process.

**Definition 1:** The distance between two tiles $T_a$ and $T_b$ from images $I_a$ and $I_b$ respectively, is:

$$ DT(T_a, T_b) = \sum_{i=1}^{m} d(\text{Feature}(T_a_i), \text{Feature}(T_b_i)) $$

where $T_{a_i}$ and $T_{b_i}$ are sub-tiles of $T_a$ and $T_b$ respectively, $m$ is the number of unique leaf nodes in the tiles’ tree structures at any hierarchical levels (if already at the leaf level, $m = 1$), the distance function $d$ is to be instantiated with some particular measure based on the result of the feature extraction done by the $\text{Feature}$ function on the tiles, e.g., BIC’s $d\text{Log}()$ function defined in the previous section.

**Definition 2:** The penalty for a certain tile $i$ from a database image after $k$ iterations is defined as:

$$ TP_i(k) = \left\{ \begin{array}{ll} \frac{\sum_{i=1}^{n} \exp(DT(T_i, I_0^i))}{\sum_{j=0}^{NT} W_j \times DTS(T_j, IS^+(k))} & \text{if } T \text{ is at full tree level} \\ \frac{\sum_{i=1}^{n} \exp(\min_{j=1}^{NT} DT(T_i, I_j^i))}{\sum_{j=0}^{NT} W_j \times DTS(T_j, IS^+(k))} & \text{if } T \text{ is at the subtree level} \end{array} \right. $$

where $NT$ in this case is the number of tiles at the current subtree level.

Assuming that $I$ is one of the identified positive example images, we can compute the tile penalty of image $I$ which consists of tiles $\{T_0, T_1, \cdots, T_{NT}\}$. The user provides positive and negative example images during each $k^{th}$ iteration of feedback, denoted respectively as $IS^+(k) = \{I_1^+(k), \cdots, I_p^+(k)\}$ and $IS^-(k) = \{I_1^-(k), \cdots, I_q^-(k)\}$, where $p + q$ is typically much smaller than the size of the database.

Based on the above preparations, we now come to the definition of tile penalty.

**Definition 4:** For all images (only being positive), the tile penalty of $T_i$ after $k$ iterations of feedback is computed (and normalized) as:

$$ TP_i(k) = \frac{W_i \times DTS(T_i, IS^+(k))}{\sum_{j=0}^{NT} (W_j \times DTS(T_j, IS^+(k)))} $$
where $W_i = 1 - \frac{DTS(T_i, IS^+(k))}{\sum_{j=0}^{N} DTS(T_j, IS^-(k))}$. acts as a penalty, reflecting the influence of the negative examples.

This implies the intuition that a tile from a positive example image should be penalized if it is similar to negative examples. Basically, we compute the distances $DTS$ between a particular tile $T$ and the positive image set $IS^+$ as well as the negative image set $IS^-$ respectively to update the penalty of that tile from a positive example image. The inverse of the tile’s distance from the negative image set is used to weight its corresponding distance from the positive image set.

Let us now illustrate the above methodology with a simple example, which also motivates the notion of tile penalty. For simplicity, assume that the color palette consists of only three colors: black, gray and white. Figure 6 shows the top 3 retrieved images and the user’s feedback judgement. Image $I_1$ is marked as a positive example since it actually contains the query image, which exactly represents the sub-image retrieval problem we are dealing with. Image $I_2$ is also marked as a positive example because it is the enlargement of the query image (and therefore containing it as well). For the sake of illustration, assume a two-level multi-cale representation of database images is used as in Figure 7.

The tile penalties for tiles per database image are initialized as 0.1 for the 10 tiles, i.e., $TP_i(0) = 0.1, i \in [0, 9]$. Now, take tile $T_1$ for example. According to Definition 3, we need to compute the distances $DTS$ between $T_1$ and the
positive/negative image set. In order to do this, firstly, the distances between $T_1$ and all tiles at the corresponding subtree levels of all the images in the positive/negative image set should be obtained by Definition 1. Then, using Definition 4 the new penalty of $T_1$ is updated from 0.1 to 0.090 correspondingly. The penalties for other tiles is updated in the same way during each feedback iteration. We illustrate the new values of all tile penalties for database image $I_1$ as a positive example after one feedback iteration in Figure[7] We can see that after the user provides feedback information, some tiles lose some weight while others gain. For instance, $T_1$, $T_2$, $T_3$ and $T_9$ receive less penalties now because they only contain the color of grey and/or black which is/are also in the query. $T_0$, $T_4$, $T_5$, $T_7$ and $T_8$ are penalized more since they all contain the color white. The new weights for these tiles generally follow the trend that more percentage of white color more penalty. $T_6$, which is a rotation of the query image maintains its weight for this iteration. This means that our system is to some extent also capable of perceiving changes such as rotation. Besides, for a closer look at the updated tile penalties of positive image $I_1$, $T_1$ receives more penalty than $T_3$ now although they are similar to the query image in the same degree. Note that, according to Definition 4, both the positive and the negative example images are used to calculate new tile penalties. And we penalize a tile more if it is also somewhat more similar to the negative example images compared with other tiles in the positive example image. Thus it is reasonable that the tile penalty for $T_1$ appears higher than that for $T_3$ after feedback learning, since $T_1$ contains some black color which is also in the negative example image $I_3$ while $T_3$ contains only the grey color.

3.2 Query Feature Update

The relevance feedback process using query refinement strategy is based on the tile re-weighting scheme and all positive and negative example images. The main concern is that we need to maintain as much as possible the original feature of query image while introducing new feature elements that would capture more new relevant images. Considering the hierarchical tree structure of the query image, we use the most similar tile (with minimum tile penalty) at every subtree level of each positive image to update the query feature at the corresponding subtree level.

Definition 5: The updated query feature after $k$ iterations is:

$$q_{i}^{k}[j] = \frac{\sum_{i=1}^{p}(1 - TP_{min_i}(k)) \times Pos_{i}^{k}[j]}{\sum_{i=1}^{p}(1 - TP_{min_i}(k))}$$

where $q_{i}^{k}$ is the new feature with M dimensions for a subtree (tile) at the $l^{th}$ level of the tree structure for the query image after $k$ iterations, $TP_{min_i}(k)$ is the minimum tile penalty for a subtree (tile) found at the $l^{th}$ level of the tree structure for the $i^{th}$ positive image after $k$ iterations, $Pos_{i}^{k}$ is the feature for the subtree (tile) with minimum tile penalty at the $l^{th}$ level of the $i^{th}$ positive
image’s tree structure after \( k \) iterations, and \( p \) is the number of positive images given by the user at this iteration. \( \bullet \)

Intuitively, we use the weighted average to update the feature for a subtree (tile) of the query, based on the features of those tiles that have minimum tile penalties within respective positive images. In this way, we try to approach the optimal query that carries the most information needed to retrieve as many relevant images to the query as possible.

### 3.3 Image Similarity

With the updated query feature and tile penalties for positive images, we can now define the distance between images and the query for ranking evaluation at each feedback iteration. In order to locate the best match to the query sub-image, our image similarity measure tries to find the minimum from the distances between the database image tiles and the query (recall that both the database image and the query sub-image have been modeled by the tree structure in the same way) at corresponding hierarchical level in the tree structure, weighted by the tile penalty of corresponding database image tiles.

**Definition 6:** The distance between the (updated) query image \( Q \) and a database image \( I \) at the \( k^{th} \) iteration is:

\[
DI_k(I, Q) = \min_{i=0}^{NT} TP_i(k-1) \times DT(I_i, Q_j)
\]

where \( NT + 1 \) is the number of all subtrees in the tree structure (tiles) of a database image, and \( TP_i(k-1) \) is the tile penalty for the \( i^{th} \) tile of image \( I \) after \( k - 1 \) iterations. \( \bullet \)

For the comparison of full tree structures, \( i = 0 \) and \( j = 0 \), indicating both the full tree structure of the database image and the query image. For the comparison of subtree structures, \( i = 1..N_l \) for each \( 1 \leq j \leq (L-1) \), where \( N_l \) is the number of subtree structures at the \( l^{th} \) level of the tree structure and \( L \) is the number of levels of the tree structure, mapped from the hierarchical partition. \( j \) indicates the subtree structure at a particular level of the query image’s tree structure, as a result of shrinking the original query tree structure to make the comparison with the subtree structures of database images comparable.

Finally, the overall relevance feedback process for the CBsIR system can be summarized in the following algorithm:

1. The user submits a query (sub)-image.
2. The system retrieves the initial set of images using the proposed similarity measure, which consists of database images containing tiles similar to the query sub-image.
3. The system collects positive and negative feedback examples identified by the user.
4. For each positive image, the tile penalties of those tiles representing this image using positive examples and negative examples is updated.
5. The system updates the query using positive images and their newly updated tile penalties.

6. The revised query and new tile penalties for database images is used to compute the ranking score for each image and sort the results.

7. Show the new retrieval results and, if the user wishes to continue, go to step 3.

4 Experiments and Results

Before going further let us define the metrics we use to measure retrieval effectiveness. For certain applications, it is more useful that the system brings new relevant images (found due to the update of query feature from previous feedback) forward into the top range rather than keeping those already retrieved relevant images again in the current iteration. For other applications, however, the opposite situation applies, the user is more interested in obtaining more relevant images during each iteration keeping those s/he has already seen before. Given these observations, we use two complementary measures for precision and recall as follows:

1. New Recall: the percentage of relevant images that were not in the set of the relevant images retrieved during previous iterations over the number of relevant images in the answer set. (Measured only after the first iteration, i.e., after the first feedback cycle.)

2. New Precision: the percentage of relevant images that were not in the set of the relevant images retrieved during previous iterations over the number of retrieved images at each iteration. (Also measured after the first iteration.)

3. Actual Recall: the percentage of relevant images at each iteration over the number of relevant images in the answer set.

4. Actual Precision: the percentage of relevant images at each iteration over the number of retrieved images at each iteration.

The new recall and precision explicitly measure the learning aptitude of the system; ideally it retrieves more new relevant images as soon as possible.

Moreover, we also measure the total number of distinct relevant images the system can find during all the feedback iterations. This is a history-based measure that implicitly includes some relevant images “lost” (out of the currently presented images) in the process. We call them cumulative recall and cumulative precision defined as follows:

1. Cumulative Recall: the percentage of distinct relevant images from all iterations so far (not necessarily shown at the current iteration) over the number of relevant images in the predefined answer set.
Table 1: Cumulative/New/Actual Recall and Precision

| Iteration | Relevant Retrieved | Cumulative Recall/Precision | New Recall/Precision | Actual Recall/Precision |
|-----------|-------------------|-----------------------------|----------------------|-------------------------|
| 1         | A                 | 33.33%/20%                  | -/-                  | 33.33%/20%              |
| 2         | A                 | 33.33%/20%                  | 0%/0%                | 33.33%/20%              |
| 3         | B,C               | 100%/60%                    | 66.67%/40%           | 66.67%/40%              |

2. **Cumulative Precision**: the percentage of distinct relevant images from all iterations so far over the number of retrieved images at each iteration.

Table 1 exemplifies the measures mentioned above, assuming the answer set for a query contains 3 images A, B, C and the number of returned (presented) images is 5.

In addition to the above measures, we also evaluate storage overhead and query processing time.

We test the proposed relevance feedback approach using a heterogenous image dataset consisting of 10,150 color JPEG images: a mixture of the public Stanford10k dataset and some images from one of COREL’s CD-ROMs, each of which falls into a particular category—we use 21 such categories. Some categories do not have rotated or translated images, but others do. On average, each answer set has 11 images, and none of the answer sets has more than 20 images, which is the amount of images we present to the user for feedback during each iteration. It is important to note that the queries and answer sets are not part of the Stanford10k dataset in order to minimize the probability that other images, not contained in the expected answer set, could also be part of the answer but not accounted for. We manually crop part of a certain image from each of the above categories to form a query image set of 21 queries (one for each category). Images of the same categories serve as the answer sets for queries (one sample query and its corresponding answer set are shown in Figure 1). The size of the query image varies, being on average 18% the size of the database images. The following performance results are collected from the online demo available at http://db.cs.ualberta.ca/mn/CBIR.html. (An sample of the two initial iterations using our system is presented in the Appendix.)

In our experiments, the maximum number of iterations explored is set to 10 (users will give feedback 9 times by pointing out which images are relevant (positive)/irrelevant (negative) to the query) and we present the top 20 retrieved images at each iteration. While within the same query session, the information collected at one step of the relevance feedback phase is used in the next step (as indicated in the definitions presented in Section 3), the information collected across different query sessions is not integrated into the search for the next
Table 2: How fast the original is ranked within the top 20 images.

| # of colors in BIC | Average # of iterations needed |
|--------------------|-------------------------------|
| 64 quantized colors| 1.1                           |
| 16 quantized colors| >2.3                          |

queries – even if the very same query is submitted to the system again. I.e., we assume query sessions are independent; more specifically, once the user goes to the initial page, all accumulated learning is cleared. This consideration is based on the observation of the subjectivity of human perception and the fact that even the same person could perceive the same retrieval result differently at different times.

As discussed earlier we use BIC histograms to model the contents of an image tile. The number of quantized colors in such histograms is therefore a parameter for BIC. We use two different values for this parameter, 16 and 64 colors, in order to evaluate the influence of the underlying tile model on the overall retrieval effectiveness.

Table 2 shows how many, on average, iterations were necessary to have the original image (the one from which the query sub-image was extracted) placed within the top 20 images. It is clear that using 64 quantized colors is more efficient, as the hit rate of the original images is almost optimal. Even though this trend, i.e., the more colors the better the retrieval, is fairly intuitive, it is interesting to see that this advantage does not grow linearly with the number of colors across all experiments. That is to say, that even using a low number of colors one can still obtain fairly good results.

The retrieval accuracy using 64 quantized colors is shown in Figure 8 and Figure 9. As it can be clearly seen, after 5 iterations the system has already learned most of the information it could learn, i.e., the information gain (given by the new recall and new precision curves) is nearly null. On the other hand, after only 5 iterations the actual recall and actual precision values increased by 55% and 60% respectively. It is also noteworthy to mention that the stable actual precision value of nearly 40% is not as low as it may seem at first. The answer sets have an average of 11 images and since the user is presented with 20 images, the maximum precision one could get (on average) would be about 50% as almost half of the displayed images could not be considered relevant by construction. This interpretation leads to the proposal of the following measure:

- **Normalized Precision**: the actual precision over the maximum possible actual precision value.

Interestingly enough, careful consideration of such a measure shows that is equivalent to the usual notion of (actual) recall. Indeed, consider $R$ and $A$ to be the sets of relevant answers and the retrieved answers with respect to a given query. The actual precision is then defined as $|R \cap A|/|A|$. The maximum precision value one can obtain is $|R|/|A|$. When the former is divided by the latter one obtains $|R \cap A|/|R|$ which is precisely the definition of actual recall.
This leads to the argument that precision-based measures are not well suited for this type of scenario, where non-relevant images are very likely to be included in the answer set regardless of their relevance. The actual recall, being concerned only with the relevant images is a more realistic measure. Under this argument, 70% of stable actual recall (or normalized precision) after 5 iterations seems quite reasonable.

We also obtained about 85% for cumulative recall and about 50% for cumulative precision. The reason for the higher values than those for actual recall and actual precision is because some relevant images that may be “lost” in subsequent iterations are always accounted for in these measures.

Using 16 quantized colors, as one would expect, yields less accuracy than using 64 quantized colors. However, an interesting aspect shown in Figures [10] and [11] is that even though, the amount of information (i.e., number of colors) was reduced by 75%, the effectiveness was reduced by at most 10% compared to the values in Figures [8] and [9]. The cost of the loss of information is more clear when looking at the “learning aptitude.” Using 16 colors required twice as many iterations in order to bring the curves to a stable state. Still, this show a sublinear dependence on the number of colors: using 4 times more colors yields only 10% more effectiveness and 2 times faster learning.

Another interesting observation, which supports the main advantage of using more color for tile abstraction, can be seen when comparing the new precision and recall curves using different numbers of colors directly (Figures [12] and [13]). Up until the 4th or 5th iteration using 64 colors yields higher values, meaning that it is learning faster, after that point, it has learned basically what it could have learn. On the other hand the curve for using 16 colors shows that the method is still learning.

Figure [14] shows the average time required to process a query during each iteration, i.e., to access all disk-resident data, complete the learning from the
Figure 9: Effectiveness measures by actual precision, cumulative precision and new precision using 64 quantized colors in BIC.

Figure 10: Effectiveness measures by actual recall, cumulative recall and new recall using 16 quantized colors in BIC.
Figure 11: Effectiveness measures by actual precision, cumulative precision and new precision using 16 quantized colors in BIC.

Figure 12: New recall (defined from the second iteration) comparison using 64 quantized colors and 16 quantized colors in BIC.
Figure 13: New precision (defined from the second iteration) comparison using 64 quantized colors and 16 quantized colors in BIC.

user’s feedback at the current iteration (not applicable to the first iteration), obtain the distance between the query image and database images and sort them by their resulting ranks. The first iteration takes, on average, slightly less than 2 seconds when using 64 quantized colors and 0.6 second when using 16 quantized colors, whereas each subsequent iteration requires about 2.5 seconds and 1 second respectively for the two feature representations. This slight increase is due to the overhead for computing and updating the tile penalties at each iteration. As well, note that the gain in speed is proportional to the smaller number of colors used, i.e., using 64 colors yields a performance about times slower than using only 16 quantized colors.

Extracting image features from the image database, applying the BIC method, and generating the metadata file requires about 0.15 secs/image on a computer running Linux 2.4.20 with AMD Athlon XP 1900+ CPU and 1GB of main memory and is independent of the number of colors used—this procedure can be done off-line and should not be considered part of query processing overhead.

Finally, the storage cost for the disk-resident metadata is 10.5 MB (only about 20% the size of the image database), while using 16 quantized colors needs proportionally less storage, namely 2.7 MB, again proportional to the representation overhead.

5 Conclusions

In this paper we have shown, for the first time, how relevance feedback can be used to improve the performance of CBsIR. We presented a relevance feedback-based technique, which is based on a tile re-weighting scheme that assigns penalties to each tile of database images and updates those of all relevant images using both the positive and negative examples identified by the user. The user’s feed-
back is used to refine the image similarity measure by weighting the tile distances between the query and the database image tiles with their corresponding tile penalties. We combine this learning method with the BIC approach for image modeling to improve the performance of content-based sub-image retrieval. Our results on an image database of over 10,000 images suggest that the learning method is quite effective for CBsIR. While using less colors within BIC reduce storage overhead and improve speedup query processing it does not affect substantially retrieval efficiency in the long term. The main drawback is the system take longer to “learn” making the overall retrieval task a longer one.

A few possible venues for further investigation include the design of disk based access structure for the hierarchical tree (to enhance the scalability for larger databases), the use of better (more powerful yet compact) representation for the tile features, possibly removing the background of the images and the incorporation of more sophisticated machine learning techniques to shorten the gap between low-level image features and high-level semantic contents of images so as to better understand the user’s intention.

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References

[1] C. Carson, M. Thomas, S. Belongie, J. M. Hellerstein, and J. Malik. Blobworld: A system for region-based image indexing and retrieval. In Proc. of the 3rd Intl. Conf. on Visual Information Systems, pages 509–516, 1999.

[2] Z. Chen, W. Liu, F. Zhang, M. Li, and H. Zhang. Web mining for web image retrieval. Journal of the American Society for Information Science and Technology, Vol. 52, No. 10, pages 831–839, 2001.

[3] J. C. Falmagne. Psychophysical measurement and theory. In Handbook of Perception and Human Performance, Vol. I, chapter 1. Willey Interscience, 1986.

[4] T. S. Huang, et al. Learning in Content-Based Image Retrieval. In Proc. of the 2nd Intl. Conf. on Development and Learning, pages 155–162, 2002.

[5] Y. Ishikawa, R. Subramanya, and C. Faloutsos. Mindreader: Query Database Through Multiple Examples. In Proc. of the 24th Intl. Conf. Very Large Database (VLDB), pages 218–227, 1998.

[6] F. Jing, M. Li, L. Zhang, H. Zhang, and B. Zhang. Learning in Region-Based Image Retrieval. In Proc. of the 2nd Intl. Conf. on Image and Video Retrieval, pages 206–215, 2003.

[7] F. Jing, B. Zhang, F. Lin, W. Ma, and H. Zhang. A Novel Region-Based Image Retrieval Method Using Relevance Feedback. In Proc. of the 3rd Intl. Workshop on Multimedia Information Retrieval, pages 28–31, 2001.

[8] K-S. Leung and R. Ng. Multiresolution Subimage Similarity Matching for Large Image Databases. In Proc. of SPIE - Storage and Retrieval for Image and Video Databases VI, pages 259–270, 1998.

[9] J. Li, J. Z. Wang, and G. Wiederhold. IRM: Integrated Region Matching for Image Retrieval. In Proc. of the 8th ACM Intl. Conf. on Multimedia, pages 147–156, 2000.

[10] G. Lu. Multimedia Database Management Systems. Artech House, 1999.

[11] J. Luo and M. A. Nascimento. Content Based Sub-Image Retrieval via Hierarchical Tree Matching. In Proc. of the 1st ACM Intl. Workshop on Multimedia Databases, pages 63–69, 2003.

[12] M. A. Nascimento and V. Chitkara. Color-Base Image Retrieval Using Binary Signatures. In Proc. of the 2002 ACM Symposium on Applied Computing, pages 687–692, 2002.

[13] J. Rocchio. Relevance feedback in information retrieval. In The SMART Retrieval System: Experiments in Automatic Document Processing (Salton, G. eds), pages 313–323, Prentice-Hall, 1971.
Appendix

Figures [15] and [19] offer a screenshot of the online demo for a sample query during the first two iterations.
No. 1 Iteration of Search

Query Image

Top 20 retrieved DB images

CPU time: 1.89 seconds / Database size: 10,150 images

Go back to image search engine for a new query

Figure 15: Online demo using 64 colors for a sample query after the first iteration (no feedback considered)
No. 2 Iteration of Search

Top 20 retrieved IR images using Relevance Feedback

CPU time: 2.65 seconds / Database size: 10,150 images

Go back to image search engine for a new query

Figure 16: Results after second iteration, i.e., feedback provided once.