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APPLYING REFERENCE SETS IN CONTENT-BASED INTERACTIVE IMAGE RETRIEVAL

Abstract

The search for graphical objects in multimedia databases is a challenging field of current research and an emerging area of application of multicriteria decision theory. It is characterised by co-existence of qualitative, quantitative, and graphical criteria and gradual approximation of preference structures during the search. Here, we propose a new approach to image search based on preference information in form of reference images provided by the user interacting with an intelligent search system. Such information can be used in image retrieval systems with relevance feedback for complex graphical objects such as leisure facilities, human faces etc. Reference sets can be combined with any other method of content-based image retrieval (CBIR), resulting in a refined search. Computational experiments have proven that the proposed approach is computationally efficient. Finally, we provide a real-life illustration of the methods proposed: an image-based hotel selection procedure.

Keywords

Multimedia databases, content-based image retrieval, relevance feedback, multicriteria decision support, preference elicitation, reference sets.

Introduction

Multimedia technologies have been developing rapidly over the last years yielding a large number of databases containing graphical data. Tools for content-based search of graphical objects have been the subject of intensive research (cf. e.g. [1]), but their performance is still unsatisfactory for many applications. Up to now, the popular Internet search engines have been only text- or quantitative-information-based, including those that search for images. Moreover, only a few existing content-based image retrieval systems, like MARS [4, 18], MindReader [4], or VisualSeek [22] allow for an interaction with the user during the search process. The general idea of an interactive search applied therein consists in changing search parameters based on the user's assessment of the relevance of images presented by the search system in consecutive iterations of the search process.

In this paper we propose new methods of content-based image retrieval, based on elicitation of users' preferences from their interactive feedback. The new features of the approach presented here can be summarized as follows:

1. The result of the search can be either a single image satisfying best the user's expectations, a subset of mutually non-comparable images from a database closest to a set of hypothetically most desired objects, or a (partial) ranking of images.
2. Pairwise and n-to-1 comparisons of images are allowed at each iteration of search as well as an individual and group relevance assessment.
3. The characteristic low-level features of images are first calculated in the background, then their monotonicity with respect to the users' assessments is tested and the CP-net updated.
4. New images to be assessed are retrieved from the multimedia database using the partial preference information gathered so far.
5. The users can generate specific graphical queries, which play the role of reference sets (cf. [20]), and speed-up the search process.
6. One or more users can interact with the retrieval system on the same query at one time.

In Section 1, we outline existing relevance-feedback-based image retrieval methods and point out their limitations. We will show that the use of reference sets in the MCDM framework enhances the relevance feedback approach. The method which we propose in Section 2, in contrast to algorithms presented in our previous work [13], is appropriate for images that cannot be recognized by matching sub-objects and the relations between them directly. Based on the binary image data, high-level features are calculated and a subset of these features serves then as the user's criteria. The decision-making method uses reference sets, the idea introduced and investigated by Skulimowski [19, 20]. As a real-life example, we have applied the above method to hotel selection based on their photographic images.

The preference elicitation method used here should ultimately lead to a gradual approximation of a simple deterministic user-specific utility function, which represents the degree to which the images in the database correspond to the user's preferences. Recall that by a *deterministic utility function* we will call a real function $v{:}D\rightarrow I\!R$, which defines the linear order $\leq_v$ in the set of alternatives assessed (here: the set D of images in the database) and conforms to the partial order $\lesssim_p$ derived from the user's preferences, i.e.

$$u_1 \leq v\, u_2 \Leftrightarrow^{\mathrm{df}} v(u_1) \leq v(u_2) \tag{1}$$

and

$$u_1 \lesssim_p u_2 \Rightarrow u_1 \leq_v u_2$$

where u_1 and u_2 are images in the database just surveyed. Let us note that the opposite implication may not be true when the same value of v is assigned to non-comparable elements in D. The satisfaction by $\leq_v$ of the linear order properties results directly from the definition of v:

1. Completeness: $\forall\, u_1,u_2\in D$: $u_1 \leq_v u_2 \vee u_2 \leq_v u_1$
2. Reflexivity: $u_1 \leq_v u_1$
3. Transitivity: $u_1 \leq_v u_2 \wedge u_2 \leq_v u_3 \Rightarrow u_1 \leq_v u_3$.

The above conditions will be referred to as the utility theory axioms. In the sequel we will presuppose that a higher value of v denotes higher user satisfaction, therefore $u_1 \leq_v u_2$ denotes that the solution u_2 is at least as good as u_1 (weakly preferred). Level sets of a utility function will be called *indifference sets* with respect to v.

Since the relation $\leq_v$ linearly orders the set of images while a total ranking of images is rarely sought, finding v is both difficult and superfluous in most decision problems. Instead, the user wishes to select one or a few image objects $u_{c1}, u_{c2}, \ldots, u_{ck}$, out of the set of objects D such that:

$$\forall u\in\{u_{c1}, u_{c2}, \ldots, u_{ck}\}\ \ \forall x\in D\setminus\{u_{c1}, u_{c2}, \ldots, u_{ck}\}\ v(x)\leq v(u) \tag{2}$$

(the subset selection problem).

The latter property means that the above axioms of the utility function 1-3 need to be fulfilled only on a subset of D×D, i.a. it does not need to be fulfilled on $\{u_{c1}, u_{c2}, \ldots, u_{ck}\}$, which can consist of elements non-comparable with respect to v. However, since the database (including web) search engines present the result of search sequentially in a predefined order, the user always gets a ranking, even if he/she did not wish so. Therefore in image retrieval problems the total ordering introduced by the utility function v on the set of surveyed objects $D_1\subset D$ guarantees that the presentation of results is coherent with one's preferences. Moreover, the gradual approximation of v during the search process may contribute to the numerical efficiency of the selection algorithm.

1. Interactive image retrieval methods

In this section, we review methods of interactive image retrieval, point out their advantages and limitations, and give some references to existing systems which apply interaction with a user in the search process. We will refer to the method proposed by Rui, Huang and Mehrotra [17] as a typical approach to image retrieval that may be interpreted in terms of a multicriteria decision making theory. In the next subsection we will propose modifications of this method, which aim to extend its application to complex objects (i.a. with non--homogenous colour and texture). Then we will compare the performance of methods based on the approach described below with the method based on neural networks proposed in Section 2.

The selection of object features to be used for calculation of similarity between images plays a crucial role in systems for image recognition and retrieval. Much work has been done on finding the features which are most useful for recognition, i.e. those that give high similarity of objects from the same class and low similarity of objects belonging to different classes. The methodology which consists of a choice of a specific similarity measure and a scalarization method (e.g. by weighted sum of several similarity measures) before recognition (retrieval) process is referred to as the *isolated approach* [6]. In the case of image retrieval, unlike image recognition, interaction with the user is possible and even desired. Some research has, therefore, been done with a view to modifying similarity measures during the retrieval process, based on information provided by the user in interactive feedback. It is assumed that users do not have any specialised knowledge on image analysis so, in interactive feedback, they only need to provide evaluation of individual images in the form of grades which express the *relevance* of images. In each iteration, the system presents to the user several images, and the relevance information given by the user is a starting point for upgrading similarity function parameters. Therefore images presented by the system in the next iteration correspond better to the user's preferences – in other words, to what the user is looking for. Besides the parameters of similarity function, descriptors of a query object can also be modified. Starting values are calculated based on an image provided by the user (who wants to find other images similar to the one/ones he already has) or randomly chosen in the first iteration, if a query image was not provided. The term *virtual query* means the set of descriptors corresponding to a system's guess about the image the user is looking for. The concept described above is referred to as *relevance feedback* and it is depicted in Figure 1.

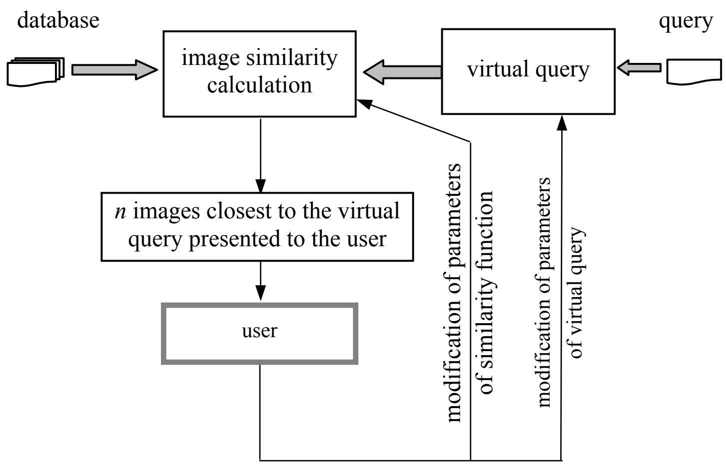


Figure 1. A typical image retrieval system with relevance feedback

Rui, Huang and Mehrotra [17] proposed an approach, where functions describing the similarity of objects are defined at three levels: 1° object – area with homogeneous colour and texture, 2° feature – e.g. colour or texture, 3° feature representation – e.g. colour histogram or average value of Gabor transform for a given area. They assume that the user's utility function is a linear combination of preferences concerning image features (like colour, texture or shape) – for example shape is k_1 times more relevant than texture. Moreover, they assume that preferences for a specific image feature are a linear combination of similarities of feature representations – for example for shape, the Hausdorff distance (cf. e.g. [14, 11]) is k_2 times more relevant than similarity of Fourier descriptors. Coefficients (in our case k_1 and k_2) can be modified in every iteration of algorithm based on *relevance feedback*, provided by the user.

Based on the assumptions given above, the distance between the query object q and the model m can be expressed as a linear combination of functions Ψ_i, which define the distance for feature representation i:

$$d(q,m) := \sum_{i=1}^{I} u_i \Psi_i(q_i, m_i, P_i) \tag{3}$$

where q and m denote the query object and model, q_i and m_i are representations (vectors, with different dimensions for different i) and P_i is a set of parameters of metric in the *i-th* representation space. For example, if the by weighted

Euclidean distance is used as a scalarizing function, P_i are weights $w_{i,j}$ of components of representation i. The calculation of parameters of similarity functions can thus be formulated as the following minimization problem:

$$\sum_k \sum_{i=1}^{I} \pi_k u_i \Psi_i(q_i, m_i^{(k)}, P_i) \longrightarrow \min_{u_i, q_i, P_i} \tag{4}$$

where π_k defines the degree of k-th image relevance for the user, which is positive for *relevant*, zero for *indifferent* and negative for *non-relevant* images (i.e. images with negative relevance, which are examples of what the user is not looking for).

When optimal parameters u_i*, q_i*, P_i* are selected based on (4), the object sought is a solution to the optimization problem:

$$\rho(k) := \sum_{i=1}^{I} u_i^* \Psi_i(q_i^*, m_i^{(k)}, P_i^*) \longrightarrow \min_k \tag{5}$$

K objects with the smallest value of ρ are presented during an interactive procedure to the user, who can again assign to them a degree of relevance in order to recalculate optimal search parameters according to (4) and perform the next iteration of the algorithm.

The formulation of the above problem (3)-(5) corresponds obviously to the distance scalarization problem, well-known in the MCDM theory. In the relevance feedback approach to image retrieval the assignment of weights and scale coefficients is purely heuristic and the researchers clearly have not yet used any virtues of multicriteria analysis. Many authors refer to the Rocchio formula (cf. e.g. [4, 6, 8, 17, 21]). The idea proposed by Rocchio in [11] is based on moving a virtual query towards the centre of gravity of *relevant* objects (in the descriptors' space) and in the opposite direction to the centre of gravity of *non-relevant* objects:

$$q_i' = \alpha q_i + \beta \frac{1}{\# M_R} \sum_{n \in M_R} m_i^n - \gamma \frac{1}{\# M_{NR}} \sum_{n \in M_{NR}} m_i^n \tag{6}$$

where α, β and γ are parameters determining what part of the modified query *q'* comes from the original query (if provided), *relevant* and *non-relevant* objects – provided by user feedback.

The Rocchio formula defines how to modify descriptors of the query object but does not solve the problem of how to find parameters of similarity function. This has been done by further heuristics methods, cf. [11]. Ishikawa, Subramanya and Faloutsos in [4] gave analytical solution of the problem, but only for a specific class of similarity functions. Nevertheless, the concept of relevant, non-relevant objects and the successful use of direction of improvement between the sets of such objects, together with the direct correspondence to the distance scalarization problem of (3)-(5), gives a hint of the use of reference sets, as described in [19] and [20].

The methods described above are based on the assumption that the user is looking for an object with pre-specified values of descriptors and his/her utility function is monotonically decreasing with the distance between the vector of descriptors of a query and retrieved object. The choice of a distance influences the choice of a utility function and it is very limited: indifferent sets are (non-dominated) parts of spheres in the selected metric. The assumption that they have such a shape is technical and does not follow from other properties of the image retrieval problem, thus cannot be regarded as justified. In real-life problems the utility function may be non-convex – depending on the structure of preferences. For example, if the user wants to find one of several objects (the case of several queries combined with *OR*), for every query component there is a corresponding local maximum of the utility function.

Above we have presented the typical approach to the image retrieval problem with relevance feedback. This methodology has several drawbacks, which may lead to inconsistent selection processes, specifically:

– the assumption of linearity of user's preferences is not justified; on the contrary, the experiments indicate that in most cases these preferences are nonlinear,
– in the methods cited above, search results not only depend on the ordinal structure of ranks assigned by the user to objects, but also on their values. This is incoherent with the basic assumptions of utility theory,
– the assumption that any object the user is looking for can be represented by a single point in feature space does not always correspond to real-life situations.

Therefore in the subsequent sections we propose an extension of the relevance feedback approach by using the specific graphical queries originating from the reference sets method in MCDA.

2. Image retrieval methods based on reference sets

Reference sets (cf. [19], [20]) have been originally designed to support industrial design and financial decisions. However, as we will show below, they are very well suited as a selection supporting tool in interactive image retrieval processes. Recall that *reference sets* are defined as sets of points in the criteria space with similar levels of utility. Skulimowski defines four basic types of reference sets in the monograph [19], cf. also [20]:

– A_0 – bounds of optimality – upper (in case of maximisation of criteria) borders of area where optimisation of criteria makes sense.
– A_1 – *target points* – goals of optimisation.
– A_2 –*status quo solutions* – existing solutions, which should be improved in optimisation process or lower bounds of the set of satisfactory solutions.
– A_3 – *anti-ideal point* – solutions to avoid.

The above sets can be further split into subclasses. All or only a few classes of reference sets may occur in a decision problem, while the consistency of problem formulation imposes a set of conditions to be fulfilled by the reference sets (cf. [20]).

The reference sets are always defined in the context of a multicriteria optimization problem, i.e.:

$$(F: D \rightarrow E) \rightarrow max \qquad (7)$$

where $F=(F_1,\ldots,F_N)$ are criteria to be optimised, E is the space of criteria values ordered by a partial order "≤" which is consistent with the preference structure (1).

Let us recall that the solutions to 00 are called "Pareto-optimal". We will show below analogies between decision support systems based on reference sets and image retrieval systems with relevance feedback. It should be noted that images in a database can be seen as elements of the set of feasible solutions. Therefore, we will redefine the interpretation of reference sets in the context of image retrieval:

– A_0 is a set of graphical queries provided by the user. We assume that the goal of the user is to find an image which is most similar to one of his queries. When the user cannot provide a query, then $A_0=\varnothing$.
– A_1 is a set of reference images ranked by the user as *relevant at the most desired level*.
– A_2 is a set of images ranked by the user as *relevant*.
– A_3 is a set of images ranked by the user as *irrelevant*.
– A_4 is a set containing images ranked by the user as *anti-relevant*, i.e. characterised by attribute values opposite to those sought.

Moreover, we assume that the vector criterion F in 0 need not be *a priori* known to the user, as the explicit user preferences constitute the primary background information. The present approach bases on an assumption that the criteria can be constructed gradually using the preference information elicited during the search process. Thus even the number of relevance criteria cannot be assumed to be a priori known as various classes of graphical objects may be characterised by different sets of features and coefficients.

2.1. Elimination of dominated solutions

In an image retrieval system with a variable number of criteria, not all dominated solutions can be rejected, because some of them can become non--dominated (Pareto-optimal) in next iterations of the search process. For example, when the new criterion F_3 is added in the problem $(F_2, F_2,) \rightarrow \max$, a previously dominated solution *b* with $F_3(b) > F_3(a)$ for all $a \in D$ will become non-dominated. In order to avoid a premature elimination of solutions which are temporarily dominated, in our algorithm we will eliminate only solutions dominated by images assigned by the user to sets A_3 or A_4.

Sets A_1 to A_4 can change during the search process. In every iteration, *K* solutions are presented (e.g. K=12) and assigned by the user to one of sets Ai. We assume that solutions in *i*-th iteration are at least as good as in previous iterations, therefore the solution assigned to set Ai cannot be later assigned to A_j for j<i – therefore we can eliminate solutions dominated by images from sets A3 or A4 because they cannot be assigned in the future to A1 or A2. The opposite situation is also possible: objects originally ranked as *relevant* among *K* randomly chosen images can be later ranked as neutral.

2.2. Image feature and selection of criteria

Criteria used for ranking images according to user preferences are modified in every iteration based on user's evaluation of images and are calculated based on subset of image features ς. The selection of image features depends on the class of images; we present the feature set for hotel selection in Section 3.3.

Let us denote by $u_i <A\, u_j$ the fact that solution u_i has been assigned by the user to a reference set with an index higher than u_j. Features *f* for which it holds:

$$u_i <_A u_j \Leftrightarrow f(u_i) < f(u_i) \tag{8}$$

will be called *monotonically increasing* with respect to the user's preferences. Features for which holds:

$$u_i <_A u_j \Leftrightarrow f(u_i) > f(u_i) \quad (9)$$

will be called *monotonically decreasing*. Sets of features monotonically increasing and decreasing will be denoted by $\varsigma\uparrow$ and $\varsigma\downarrow$, respectively.

As criteria, we will select features from the set $\varsigma\uparrow$ and a decreasing function of features from the set $\varsigma\downarrow$. Utility function will then be calculated based on two criteria: distance from the set A_1 (or A_0, if it has been defined by providing virtual queries) and distance from the set A_4. Therefore utility function can be expressed as:

$$v(u) = 1 / [d(u, A_1) + h(d(u, A_4))] \quad (10)$$

where h is a decreasing function. For implementation, we used $h(x) := 1/(x+\varepsilon)$.

A resulting image retrieval algorithm with reference sets is presented below.

Algorithm 1. (interactive image retrieval with reference sets)

Step 1 Present to the user the set $S(i)$ of images (i is the number of the iteration), ordered according to ranking based on recently calculated information about user preferences. In the first iteration, the set $S(i)$ is chosen randomly from the database.

Step 2 The user assigns elements of the set $S(i)$ to the reference sets.

Step 3 Calculate the set of features monotonically increasing $\varsigma\uparrow$ and monotonically decreasing $\varsigma\downarrow$.

Step 4 Calculate criteria values based on $\varsigma\uparrow$ and $\varsigma\downarrow$, estimation of utility function v and calculation of utility of images from the set $S(i)$.

Step 5 Check if $\forall\ u_1, u_2 \in S(i)\ u_i <_A u_j \Rightarrow v(u_1) > v(u_2)$. If the condition is not fulfilled, the user should redefine reference sets, and we return to Step 2.

Step 6 Assign images dominated by the elements of $\{A_3(i) \cup A_4(i)\}$ to the set of dominated solutions.

Step 7 Calculate utility for all images in database.

Step 8 Rank all images in database based on utility function.

Step 9 Assign $i=i+1$, return to Step 1.

■

3. An example of real-life image retrieval with reference sets

To evaluate the above-presented method, we have developed an interactive system Scene Retrieval for Matlab environment. Tests have been done for image-based hotel search. The set of image features depends on a specific application and class of images. The feature set for our application is presented in Table 1.

Table 1

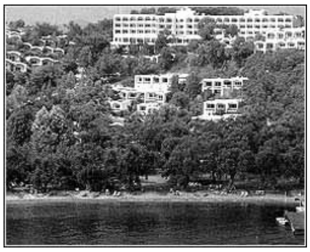
Set of image features for favourite hotel retrieval

No.	Elementary criteria/feature description
1	area of hotel divided by area of image
2	area of forest divided by area of image
3	area of meadow divided by area of image
4	area of sea divided by area of image
5	area of swimming pool divided by area of image
6	area of beach divided by area of image
7	area of forest divided by area of hotel
8	area of meadow divided by area of hotel
9	area of sea divided by area of hotel
10	area of swimming pool divided by area of hotel
11	area of beach divided by area of hotel
12	number of segmented parts of image recognized as parts of hotel
13	width of hotel divided by width of image
14	height of hotel divided by height of image
15	height of hotel divided by its width
16	width of forest areas divided by width of image
17	height of forest areas divided by height of image
18	value of feature17 divided by value of feature 16

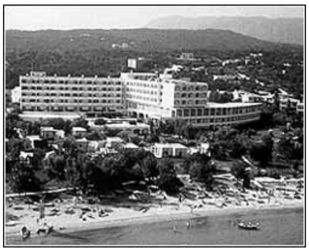
In Figure 2, we can see 6 out of 137 images of Greek hotels, available at www.dilos.com.

a

b



c



d

e

f

Figure 2. Images of hotels presented to the user in the first iteration of search algorithm

Let us assume that the user – intentionally or not – selects a hotel when the image contains a lot of greenery (the main user criterion) and with small buildings (additional criterion), therefore images are assigned:

– to the set A_1 if the image contains forest and small buildings,
– to the set A_2 if the image contains forest and big buildings,
– to the set A_3 if the image contains no forest (or a small area of forest) and small buildings,
– to the set A4 if the image contains no forest (or a small area of forest) and larger buildings.

In a single iteration, six images are presented to the user. This number, determined from the point of view of efficiency of the decision-making process, is a result of experiments aiming at minimizing the overall reflexion time of the user. Images presented in the first iteration are shown in Figure 2. Reference sets A_1,...,A_4 assigned by the user to these images are shown in Table 2.

Table 2

Preferences of the user, expressed by assignment of images to reference sets

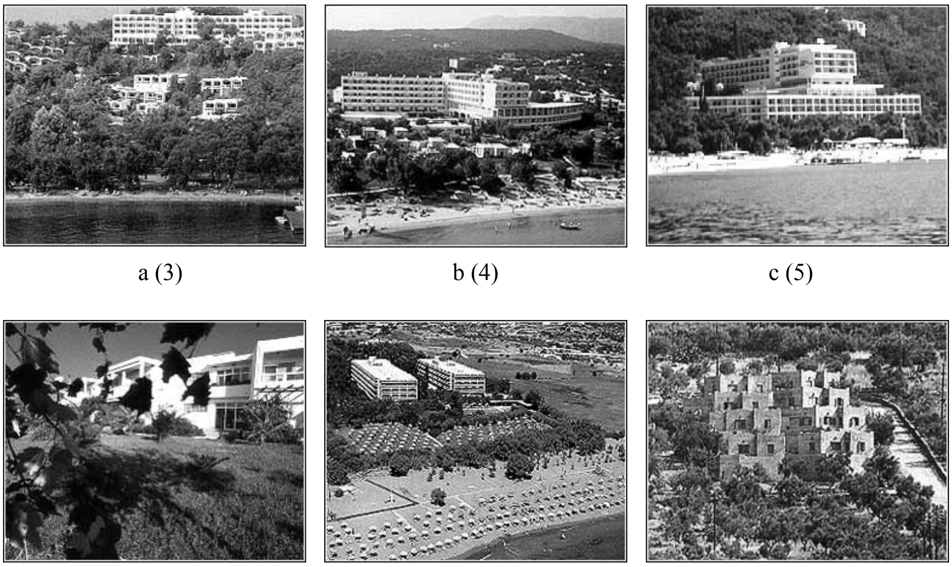
No. of image	No. of reference set	Filename
1 (a)	2	1811.jpg
2 (b)	4	1814.jpg
3 (c)	1	1818.jpg
4 (d)	1	1824.jpg
5 (e)	2	1831.jpg
6 (f)	2	1836.jpg

Based on data presented in Table 2, the Algorithm 2 automatically found features that change monotonically with a change of utility value. Features monotonically increasing (i.e. with smaller value for higher level of user's satisfaction) are: 1 and 14 and features monotonically decreasing are 2, 7, 16 and 17 – cf. Table 1. The ranking of 6 images with the lowest value of utility function is presented in Table 3 and in Figure 3.

Table 3

Results of search: 6 images with the lowest value of estimated utility

No. in ranking	No. in database	Utility	Filename
2	3	0.0053	1818.jpg
3	4	0.0494	1824.jpg
4	5	0.8899	1831.jpg
5	111	0.9782	1939.jpg
6	33	1.0472	1143.jpg
8	36	1.2404	1156.jpg



a (3) b (4) c (5)

d (111) e (33) f (36)

Figure 3. Search results – 6 images with the lowest value of utility function in brackets: numbers of images in the database

Experiments, such as the one described above, and others, which can be found in [12], show that the system is able to elicit user's preferences based on his/her assessment of several exemplary images. Preferred image features are calculated correctly (cf. Table 4) and retrieved images correspond to user's expectations, therefore we can claim that the method proposed can be useful for interactive image retrieval systems.

Table 4

Image features preferred by the user, automatically calculated by the system (reference to the example in Figures 2-3)

Image features preferred by the user	– large area of forest (the main criterion) – small size of buildings (additional criterion)
Preferred image features calculated by the system based on 6 examples	Low value of: – area of hotel divided by area of image – height of hotel divided by height of image High value of: – area of forest divided by area of image – area of forest divided by area of hotel – width of forest areas divided by width of image – height of forest areas divided by height of image

Table 4 contd.

Preferred image features calculated by the system based on 12 examples	Low value of: – width of hotel divided by width of image – height of hotel divided by its width High value of: – width of forest areas divided by width of image – height of forest areas divided by height of image

The above preference elicitation algorithm is just a single component of the entire image retrieval system. Image analysis is another crucial part and overall usefulness of the above method depends on correct classification of image objects (cf. [15]). The performance of an image retrieval system is therefore dependent on the low-level feature detection and image recognition methods and strongly depends on the properties of the class of images where the search is performed.

Final remarks

In the above approach to the image retrieval, which most likely appears as a problem of selecting an image from a multimedia database, we have successfully applied the reference sets – a MCDM tool originally designed for other types of decision-making problems. Conversely, it may turn out that the methods of visual information extraction might be used in multicriteria decision-making problems in other areas of application. In particular, when the set of feasible alternatives may be characterized by a set of elementary features, they might be implicitly extracted as used as pre-criteria by a decision support system. Based on users' feedback, an automatic elaboration of *ceteris paribus* (CP) nets (cf. e.g. [2]) for each pre-pre-criterion might be possible and – in turn – might support an interactive search for a compromise solution. As a potential field of application of such methods one can mention the situation where a complex technical system is to be chosen by a person or a group of decision makers without an adequate technical knowledge.

The most straightforward application of relevance feedback methods enhanced by the reference sets approach presented here is web visual object search systems. At the time when this paper was written (May 2007) the commonly used systems did not allow to define graphical queries directly, which indicated a lack of adequate image search mechanisms. A prototype

(Matlab) implementation of the algorithms here presented ([21]) points out that the use of MCDM methods is very promising in the field of multimedia databases.

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