Egyptian Informatics Journal (2017) 18, 1–9

Cairo University

Egyptian Informatics Journal

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FULL-LENGTH ARTICLE

# Distance selection based on relevance feedback in the context of CBIR using the SFS meta-heuristic with one round

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Received 20 August 2015; revised 24 June 2016; accepted 1 September 2016
Available online 19 October 2016

**KEYWORDS**

CBIR;
Distance-selection;
Relevance feedback;
SFS meta-heuristic;
Precision and Recall

**Abstract** In this paper, we address the selection in the context of Content Based-Image Retrieval (CBIR). Instead of addressing *features' selection* issue, we deal here with *distance selection* as a novel paradigm poorly addressed within CBIR field. Whereas distance concept is a very precise and sharp mathematical tool, we extend the study to weak distances: Similarity, quasi-distance, and divergence. Therefore, as many as eighteen (18) such measures as considered: distances: {Euclidian, ...}, similarities{Ruzika, ...}, quasi-distances: {Neyman-$X^2$, ...} and divergences: {Jeffrey, ...}. We specifically propose a hybrid system based on the Sequential Forward Selector (SFS) meta-heuristic with one round and relevance feedback. The experiments conducted on the *Wang database* (*Corel-1K*) using color moments as a signature show that our system yields promising results in terms of effectiveness.



## 1. Introduction

As any information retrieval system, a Content Based-Image Retrieval (CBIR) system aims at satisfying the user need through extracting, from the image database, a subset of images deemed as similar to the submitted query, let alone relevant to the user expectations. For doing so, a CBIR system utilizes some low-level features such as color, e.g. [1], texture, e.g. [2,3] and shape, e.g. [4]. A comparative study of some CBIR works is reported in [5]. Unfortunately, users are still usually unsatisfied with results answered by actual CBIR systems, owing to the semantic gap problem. Indeed, there is a gap between the relevance notion from the user viewpoint and the automatic relevance of the system. For improving results given by a CBIR system, one must, therefore then, reduce the gap between the two previous cited kinds of relevance. The relevance from the user perspective is related to what he/she has in his/her mind about his/her needs, whereas relevance from the system viewpoint is related to the query.

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Peer review under responsibility of Faculty of Computers and Information, Cairo University.

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http://dx.doi.org/10.1016/j.eij.2016.09.001
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Among suggested solutions to the semantic gap, some authors used multiple query techniques, e.g. [6].

A basic key affecting the system relevance, and in consequence its accuracy, is the matching measure to work with. Review of literature shows that there are many matching measures ranging from distances and similarities to quasi-distances and divergences. To the best of our knowledge, few works have addressed the matching measure as a point of interest in the context of CBIR, e.g. [7–10]. The question to ask then is what matching measure should one use when building a CBIR system. Similarly, what matching measure should be used with respect to a specific query? This question leads consequently to the legitimate issue of *matching measure selection*.

A natural answer to the question of matching measure selection is the learning process. Review of literature shows that there are two manners for implementing the matching measure selection in the CBIR field: utilizing selection problem tools or learning through relevance feedback.

The proposed work falls within both aforementioned areas of CBIR field: selection paradigm and relevance feedback. These notions are explained in the following subsections.

### 1.1. Selection paradigm

To the best of our knowledge, the selection paradigm in the CBIR field has been so far restricted to features selection aspect only, e.g. [11]. Indeed, many authors have asked the following question: "which features are most suitable for a specific query?". Features selection methods search for the most relevant feature subset, belonging to the original feature space, according to a user defined criterion [12]. Features selection algorithms aim at choosing a reduced number of features that preserve the most relevant information of the dataset. Features selection is usually applied as a preprocessing step in data mining tasks by removing irrelevant or redundant features leading to more efficient and accurate classification, clustering and similarity searching processes [12]. There are three broad classes of features selection: filter methods, e.g. [13], wrapper methods, e.g. [14], and hybrid methods. Filter methods use general characteristics of the data independently of the classifier for the evaluation process. The evaluation process is classifier-dependent in wrapper methods. Finally, hybrid models use both filtering and wrapping methods for improving the performance of the selection process.

The problem with the selection tools is that the learning stage is expensive in terms of computing time. Therefore, it is done offline. In addition to that, tools, utilized in the learning stage, require evaluation according to a fitness measure. This poses other questions about the processed dataset devoted to learning. The retrieval problem, in the case of systems based on feature selection, can, therefore, be viewed as a classification problem. Evidently, in this case, the learning stage is crucial.

In this paper, we address *the matching measure selection paradigm* rather than *the feature selection paradigm*. More specifically, we aim to select, for each query, one matching measure that would be the best for a given query from the perspective of effectiveness. For doing so, we utilize the *Sequential Forward Selector* (SFS) algorithm [15,16] with one round. This choice has been motivated by the characteristic of the SFS-One-Round algorithm of being very efficient. In the following point, we explain briefly the SFS algorithm.

#### 1.1.1. SFS algorithm

In this work, we use the SFS algorithm rather than other meta-heuristic algorithms such as Genetics Algorithm and Cuckoo Search Algorithm (CSA) owing to its simplicity. Other meta-heuristics than the SFS algorithm are of course of great interest as subject of study. Indeed, review of literature reveals that there exist many meta-heuristic algorithms applied in a variety of fields, e.g. [17–20]. However, choosing the best meta-heuristic algorithm for selecting the adequate matching measure goes beyond the scope of this paper.

Because we do not want to combine matching measures, we believe that one round is enough to answer the question: "which matching measure is the best?". The pseudo code of the SFS algorithm is presented in Fig. 1. In this pseudo code, the fitness value has trade-off with the sum of the ranks of images labeled as relevant by the user. This fitness is given by the following equation:

$$fitness = 1/n * \sum_{i=1}^{n} rank(i) \tag{1}$$

where $n$ is the number of images labeled as relevant by the user.

The SFS algorithm with one round uses the pre-cited pseudo code from Step 1 to Step 4.

### 1.2. Relevance feedback

The relevance feedback concept, coming from documentary information retrieval [21,22], has received, in last few years, a lot of attention in the CBIR field, e.g. [23]. This scheme consists of receiving additional information from the user after visualizing the initial results. This additional information is simply the judgment of some visualized results by the user as relevant or non-relevant to his/her requirement. According to this judgment, the system proceeds to adjust its processing behavior for improving performances. The relevance feedback mechanism then is an additional tool for reducing the angle between the user relevance and system relevance by giving a

```
SFS Algorithm
Step 1: as initialization the algorithm starts with the following weighting (0, 0,..0) (no selected matching measure).
Step 2: each weight will be set 1 separately to generate many configurations.
Step 3: to evaluate each configuration based on the fitness.
Step 4: selecting the best configuration.
Step 5: comparing the actual selected configuration with the selected configuration of the previous iteration, if there is no improvement so go to the Step 8.
Step 6: set the other weights 0 except the weight of the selected matching measures is still 1.
Step 7: go to the Step 2.
Step 8: END.
```

**Figure 1** Pseudo code of the SFS algorithm.

more clear vision on the user expectations and adjusting the inside system behavior in hope to bridge the semantic gap. Review of literature shows that there exist a lot of approaches for exploiting the feedback. The first approach consists of shifting query, in a way based on the new generated query, the images deemed as relevant by the user will be better ranked while the images judged as non-relevant will be ranked on the bottom. Query Point Movement [24], Standard Rocchio's Formula [25], and Adaptive Shifting Query [26] are three alternatives of this approach. Feature weighting [27], which is close to the feature selection, and the optimization of the parameters of the similarity metrics [28,29], utilizing of K-nearest Neighbors (KNN) classification algorithm [30] are other techniques for exploiting feedback. A comparative study of these approaches is given in [31]. The approach adopted in this work is close to "Optimization of the parameters of the similarity metric". This approach consists of optimizing the parameters in the case of many similarities or distances. The parameters that make the rate of images labeled as relevant by the user better than the rate of images labeled as non-relevant are the best configuration to look for.

To note that methods based on relevance feedback suffer generally from the scarcity of images being judged by the user. Generally, it is not possible to build a good model based on few deemed images which requires to enlarge the subset of judged images.

The difference between the two pre-cited approaches: *feature selection* and *learning using feedback* is that *the feature selection* is a broad approach which explores all the possible cases and proceeds to designate for each class of images the best configuration. Therefore feature selection is expensive in terms of resources especially in terms of processing time but this does not a matter owing to the fact that learning stage is done offline. For *the features weighting* based on the relevance feedback information, the task is done in deep way. In other words, the system looks for the configuration which ranks, on the top, the images deemed as relevant by the user. The learning then will be stopped when this condition is satisfied.

In this paper, we introduce a novel approach which combines the two approaches: *selection* and *relevance feedback* but we focus on the matching measure rather than features. To the best of our knowledge, the distance selection has not been addressed as a point of interest in the context of CBIR. Our proposed approach takes advantage then of both approaches: the effectiveness of selection paradigm and the efficiency of relevance feedback.

The rest of this paper is arranged as follows: Section 2 presents the proposed approach. In Section 3, we discuss the considered materials and settings. Section 4 shows experiments conducted and the obtained results. We conclude the paper with conclusion and some perspectives.

## 2. Our proposed approach

The execution scenario of our approach is as follows: after receiving the submitted query, the system answers by a set of images as initial results applying one matching measure. After that, the user has to designate some relevant images from those answered by the system. The first images not judged by the user are considered as non-relevant. The system will then

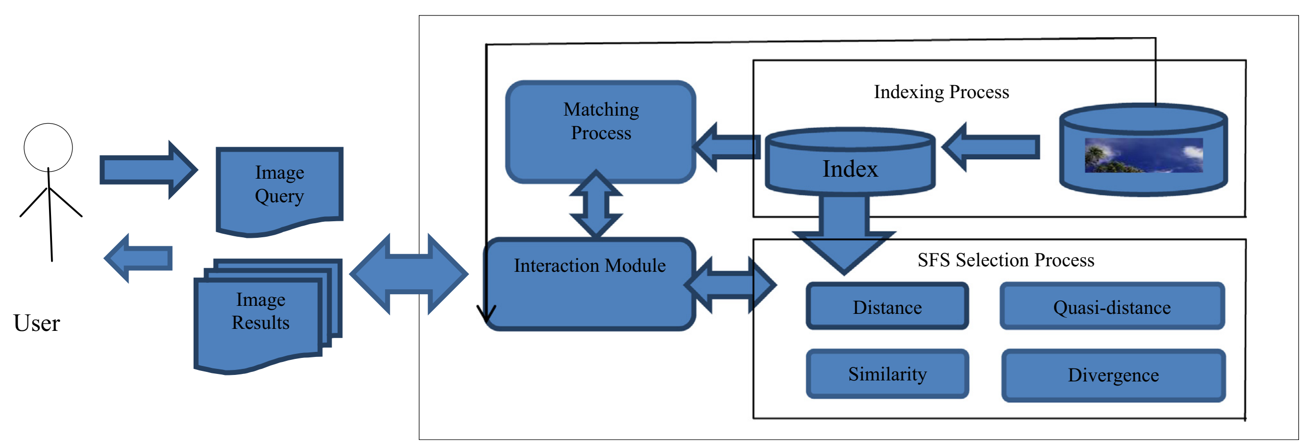


**Figure 2** General architecture of the proposed approach.

**Figure 3** Some images representing the 10 classes of the Wang database.

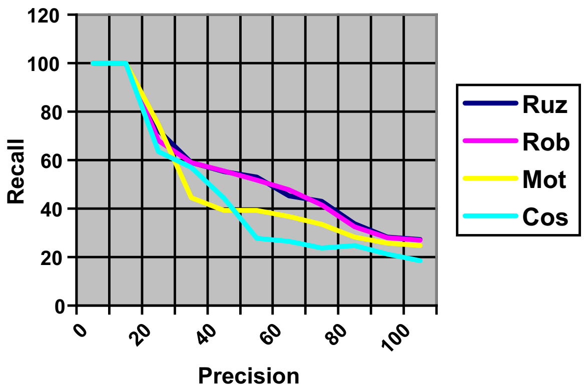


**Figure 4** Average Precision/Recall over considered similarities (Ruz: Ruzicka, Rob: Roberts, Mot: Motyka, Cos: Cosine).

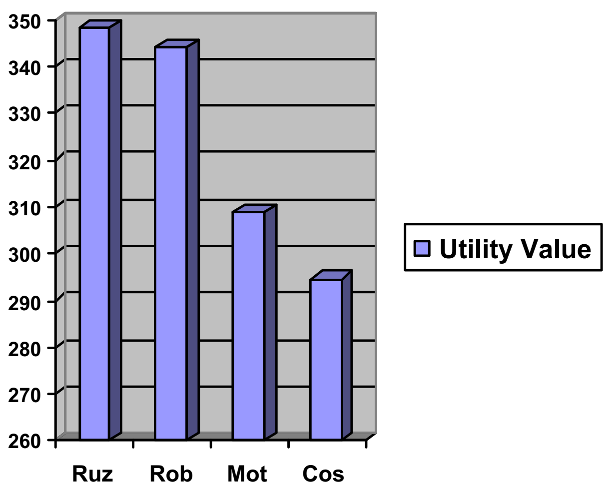


**Figure 5** Comparison between the effectiveness of similarities based on the utility concept.

launch the execution of the SFS algorithm with one round which designates the best matching measure. Selected matching measure will be then applied on the entire asked database and results will be visualized again to the user (see Fig. 2).

### 3. Settings and experiments

The results obtained in this paper are conducted on the heterogeneous *Wang database* (*Corel-1K*) [32]. This dataset is composed of 1000 images of 10 semantic classes and is widely used in the CBIR field. A sample of this base is presented in Fig. 3 where one image for each semantic class is shown. We utilize the three first low color moments [33] as a signature, 4 similarities: *Ruzicka*, *Roberts*, *Motyka* and *Cosine*, 10 distances: *Euclidean distance*, *Intersection distance*, *Sorensen distance*, *Kulczunsky distance*, *Soergel distance*, *Chebyshev distance*, *Manhattan distance*, *Squared distance*, *Mahalanobis distance*, and *Canberra*. 3 quasi-distances are used here: $X^2$ *distance*, *Neyman*-$X^2$ *distance* and *Separation distance* [34]. For the divergence, we use the *Jeffrey divergence*. All these settings are given in the following formulas:

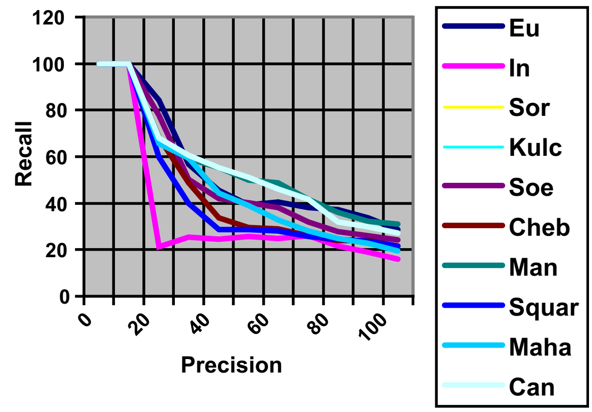


**Figure 6** Average Precision/Recall over considered distances (Eu: Euclidean, In: Intersection, Sor: Sorensen, Kulc: Kulczunsky, Soe: Soergel, Cheb: Chebyshev, Man: Manhattan, Squar: Squared, Maha: Mahalanobis, Can: Canberra).

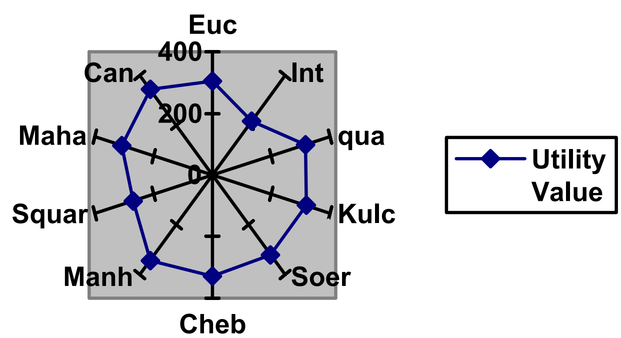


**Figure 7** Comparison between the effectiveness of distances based on the utility concept.

- The first color moment

$$m = 1/N\sum_{j=1}^{N} f_{ij} \tag{2}$$

where $N$ is the number of pixels in the image. $f_{ij}$ is the value of the pixel of $i$th row and $j$th column.

- The second color moment

$$v = \sqrt{1/N\sum_{j=1}^{N}(f_{ij} - m)^2} \tag{3}$$

- The third color moment

$$s = \sqrt[3]{1/N\sum_{j=1}^{N}(f_{ij} - m)} \tag{4}$$

- Ruzicka similarity

$$\frac{\sum \min\{x_i, y_i\}}{\sum \max\{x_i, y_i\}} \tag{5}$$

- Roberts similarity

$$\frac{\sum(x_i + y_i)\frac{\min\{xi, y_i\}}{\max\{xi, y_i\}}}{\sum(x_i + y_i)} \tag{6}$$

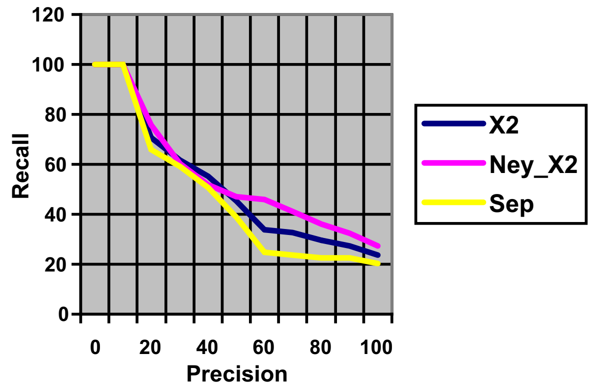


**Figure 8** Average Precision/Recall over considered quasi-distances ($X^2$: Neyman-$X^2$, Sep: Separation).

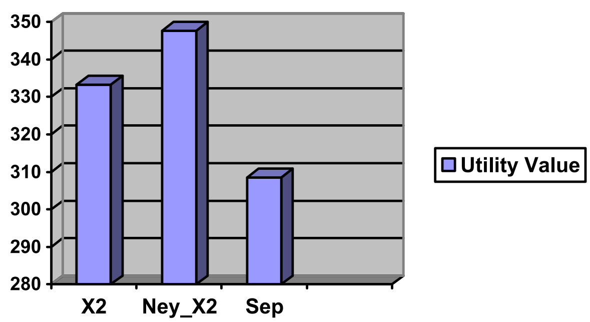


**Figure 9** Comparison between the effectiveness of quasi-distances based on the utility concept.

- Motyka similarity

$$\frac{\sum \min\{x_i, y_i\}}{\sum (x_i + y_i)} \tag{7}$$

- Cosine similarity

$$\text{cosine}(T, S) = \frac{\vec{T} \cdot \vec{S}}{\sqrt{\|\vec{T}\| \|\vec{S}\|}} \tag{8}$$

- Euclidean distance

$$\sqrt{\sum (a_i - b_i)^2} \tag{9}$$

- Manhattan distance

$$\sum |a_i - b_i| \tag{10}$$

- Intersection distance

$$1 - \frac{\sum \min\{a_i, b_i\}}{\min\{\sum a_i, \sum b_i\}} \tag{11}$$

- Sorensen distance

$$\frac{\sum |a_i - b_i|}{\sum (a_i + b_i)} \tag{12}$$

- Kulczunsky distance

$$\frac{\sum |a_i - b_i|}{\sum \min\{a_i, b_i\}} \tag{13}$$

- Soergel distance

$$\frac{\sum |a_i - b_i|}{\sum (a_i + b_i)} \tag{14}$$

**Table 1** Correspondence between the query class and the adequate matching Measure.

| Class | Africa | Bus | Monument | Horse | Dinosaur | Elephant | Flower | Mountain | Beach | Food |
|---|---|---|---|---|---|---|---|---|---|---|
| Corresponding matching formula | Ruzicka | Separation | Intersection | Separation | Kulczunsky<br>Soergel<br>Ruzicka<br>Separation | Ruzicka | Jeffrey | Cosine | Chebyshev | Roberts |

**Table 2** Precision/Recall values for each query class after applying SFS.

| Recall (%) | Precision (%) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | African | Bus | Horse | Monument | Dinosaur | Elephant | Flower | Mountain | Beach | Food | Average |
| 10 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| 20 | 100 | 100 | 10.52 | 10.52 | 100 | 100 | 100 | 100 | 100 | 66.66 | 78.77 |
| 30 | 60 | 100 | 13.63 | 15 | 100 | 100 | 100 | 60 | 16.66 | 60 | 62.53 |
| 40 | 66.66 | 44.44 | 14.28 | 19.04 | 100 | 100 | 100 | 66.66 | 18.18 | 66.66 | 59.59 |
| 50 | 55.55 | 20.83 | 17.24 | 22.72 | 100 | 100 | 100 | 29.41 | 18.51 | 71.42 | 53.56 |
| 60 | 33.33 | 22.22 | 8.82 | 10.71 | 100 | 85.71 | 100 | 31.57 | 16.66 | 60 | 46.90 |
| 70 | 25.92 | 20 | 8.43 | 12.06 | 100 | 77.77 | 87.5 | 28 | 18.91 | 43.75 | 42.23 |
| 80 | 27.58 | 19.04 | 9.41 | 12.69 | 100 | 72.72 | 80 | 28.57 | 15.09 | 25.80 | 39.10 |
| 90 | 20.45 | 20.93 | 9.67 | 11.11 | 100 | 31.03 | 75 | 27.27 | 13.63 | 25.71 | 33.48 |
| 100 | 16.94 | 10.75 | 10.41 | 10.52 | 100 | 33.33 | 47.61 | 18.86 | 14.70 | 21.27 | 28.44 |

**Table 3** Average Precision/Recall values of the best formulas against the SFS.

| Recall (%) | Precision (%) | | | | |
|---|---|---|---|---|---|
| | Ruzicka | Canberra | $X^2$ | Jeffrey | SFS |
| 10 | 100 | 100 | 100 | 100 | 100 |
| 20 | 72.20 | 68.09 | 70.83 | 82.48 | 78.77 |
| 30 | 58.89 | 60.47% | 61.64 | 59.44 | 62.53 |
| 40 | 55.35 | 55.13 | 55.34 | 45.83 | 59.59 |
| 50 | 52.91 | 51.12 | 45.34 | 41.68 | 53.56 |
| 60 | 45.36 | 46.20 | 33.87 | 40.37 | 46.90 |
| 70 | 42.92 | 41.58 | 32.67 | 35.49 | 42.23 |
| 80 | 33.83 | 31.78 | 29.51 | 32.29 | 39.10 |
| 90 | 28.29 | 29.97 | 27.33 | 30.36 | 33.48 |
| 100 | 27.28 | 27.31 | 23.54 | 24.84 | 28.44 |

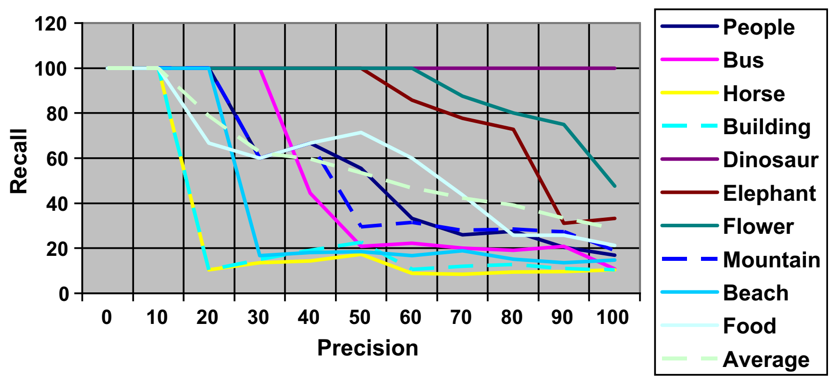


**Figure 10** Precision/Recall curves for each asked class of the Wang database after applying the SFS with relevance feedback.

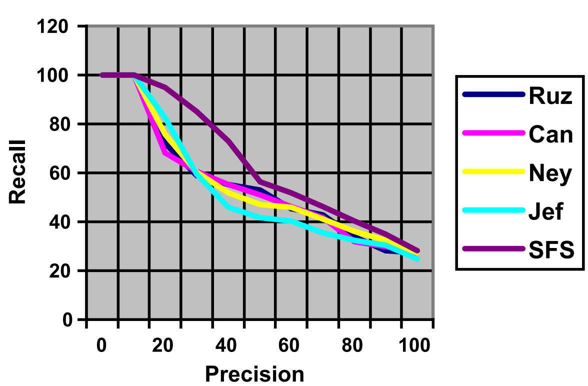


**Figure 11** SFS against the best measures in terms of average Precision/Recall (Jef: Jeffrey divergence).

- Chebyshev distance

$$\max\{|x_i - y_i|\} \tag{15}$$

- Squared distance

$$D_Q = \sqrt{(f_1 - f_2)^T A (f_1 - f_2)} \tag{16}$$

where $A = [a_{ij}]$ and $a_{ij} = 1 - \frac{d_{ij}}{\max(d_{ij})}$

- Mahalanobis distance

$$D_m = \sqrt{(f_1 - f_2)^T C^{-1} (f_1 - f_2)} \tag{17}$$

where $C$ is the co-variance matrix.

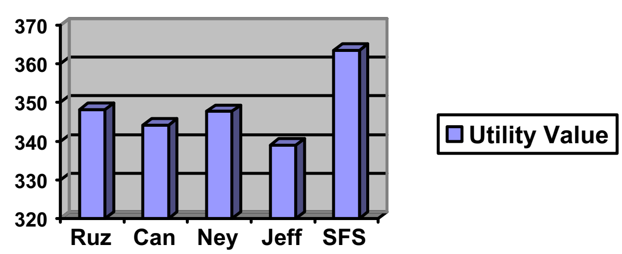


**Figure 12** The best measures against the SFS with relevance feedback.

- Canberra distance

$$\sum \frac{|a_i - b_i|}{|a_i| + |b_i|} \tag{18}$$

- $X^2$ quasi-distance

$$\sum_x \frac{(p_1(x) - p_2(x))^2}{p_2(x)} \tag{19}$$

- Neyman-$X^2$ quasi-distance

$$\sum_x \frac{(p_1(x) - p_2(x))^2}{p_1(x)} \tag{20}$$

- Separation quasi-distance

$$\max_x \left(1 - \frac{p_1(x)}{p_2(x)}\right) \tag{21}$$

**Figure 13** Results returned by the system after applying the SFS for a query belonging to the flower class (the formula chosen by the SFS is the Jeffrey quasi-distance).

- Jeffrey divergence

$$\sum_x (p_1(x) - p_2(x)) \ln \frac{p_1(x)}{p_2(x)} \quad (22)$$

The effectiveness of our system is evaluated using the Precision and Recall metrics [35]. These metrics are given as follows:

$$\text{Precision} = \text{NRIR}/\text{TNIR} \quad (23)$$

$$\text{Recall} = \text{NRIR}/\text{TNRI} \quad (24)$$

where NRIR is number of relevant images retrieved. TNIR is total number of images retrieved and TNRI is total number of relevant images in the asked database.

Even with precision/recall values, it is difficult to compare between the effectiveness of matching measures. Therefore Precision/Recall values will be changed to only one value using the Utility concept inspired from [36] as depicted by the following equation:

$$v = \sum_{s=0}^{1} P * (1 - s) \quad (25)$$

where $P$ is the *precision value* and s is a constant belongs to the range [0 1].

Fig. 4 shows the average precision/recall values of the 4 considered similarities.

Fig. 5 clearly shows the outperformance of the *Ruzika similarity* and to some extent that of the Roberts over the other similarities.

Fig. 6 depicts the average precision/recall values of the 10 considered distances.

According to Fig. 7, *Canberra* is the best distance in terms of precision.

Fig. 8 illustrates the precision/recall values of the 3 considered quasi-distances.

As described in Fig. 9, Neyman-$X^2$ is the best in terms of performance.

Table 1 shows the correspondence between the query class and the adequate matching measure found by the *SFS algorithm* of one round with relevance feedback. For the dinosaur class, there are 4 measures selected. The 4 measures yield the same high performance. Table 2 shows Precision/Recall values after applying *SFS* with relevance feedback for each query class of 10 classes of the *Wang database*.

**Figure 14** Results returned by the system without applying the SFS for a query belonging to the flower class (the formula utilized here is intersection distance).

Table 3 labels average Precision/Recall values of the best measures against applying of the *SFS algorithm* with *relevance feedback* (see Figs. 11 and 12).

According to Table 3 and Fig. 12, *SFS algorithm* of one round with relevance feedback improves the performance in terms of precision (see Figs. 13 and 14).

## 4. Conclusion

This study was focused on the paradigm of matching measure selection within the CBIR systems. The study has considered as many as 18 *matching measures*, including *similarities*, *distances*, *quasi-distances* and *divergences*. The selection process was based on the *SFS algorithm* with one round and *relevance feedback* in order to determine the best *matching measure* for a specific query. As such, we introduced a novel approach to the *distance-selection* paradigm in the context of CBIR, rather than the classical and well-known *features selection* paradigm. The obtained results show that our approach yields promising results in terms of precision, recall and utility value.

As a perspective, the results achieved will be compared to other *relevance feedback* techniques, especially in terms of distance combination, such as the "optimization of the parameters of similarities" method. Moreover, we plan to address the selection of both features and matching measures utilizing other meta-heuristic algorithms and why not addressing the selection, in the context of CBIR, of different selection algorithms.

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