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System profiles in content-based image indexing and retrieval

Esin Guldogan · Moncef Gabbouj

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Abstract In this paper, a novel study on system profiles and adaptation of parameters for end-users of content-based indexing and retrieval (CBIR) applications are presented. The main objective of the study is improving the overall CBIR application performance in different hardware platforms having different technical capabilities and conditions. We define CBIR system profiles in terms of hardware and system platform attributes and propose CBIR parameters for each profile. Hence, the study consists of two main parts: system profiling and adaptation of indexing and retrieval parameters for each profile. The proposed CBIR parameters are appropriate configurations for optimal CBIR use on every platform. The proposed parameters for each system profile are assessed over a large set of experiments. Experimental studies show that the proposed parameters for each system profile have satisfactory semantic retrieval performance, with reduced computational complexity and storage space requirement. 45 to 78% improvement is achieved in the computational complexity of the retrieval process depending on the profile.

Keywords Content-based indexing and retrieval · User hardware system profiles · Indexing and retrieval parameters · Optimization of indexing and retrieval performance

1 Introduction

The use of content-based image retrieval (CBIR) systems has become widespread during the last decade on different hardware platforms such as mobile phones. Several CBIR applications have been developed for commercial and academic purposes [1–4]. They often do not consider hardware architecture differences, and they are mostly not adaptable. Non-adaptable CBIR applications do not address effectively various user needs. User demands and expectations vary depending on the underlying hardware system (platform), which describes the set of hardware components of the device itself and can also be called hardware system in this paper. Scalability and adaptability are desired attributes of a CBIR application. Scalability refers to the ability of handling growing amounts of data and adaptability refers to adapting itself effectively to changed platforms and situations [5,6]. In this paper, we address only hardware scalability. CBIR application would be hardware scalable in the sense that its performance remains suitably efficient and practical under changing database sizes and or hardware capabilities. In addition, adaptability of a CBIR application to specific hardware architecture adds to the flexibility of the application. Adaptability here refers to the ability to select appropriate functionalities and suitable parameters in the CBIR application to fit the requirements of a given hardware system. CBIR evaluation workgroups effort stresses criteria such as the quality of adaptability of a CBIR application into a new domain [7]. They also express the importance of factors such as accuracy, speed and adaptability of CBIR applications. Datta et al. in [4] discussed significant challenges involved in the adaptation of existing image retrieval techniques to build systems that can be useful in the real world. In order to improve the scalability and adaptability attributes of a CBIR application, different hardware systems hosting the application, their limitations, capabilities, and requirements have to be taken into account. Relatively little information about CBIR users and their hardware platforms are available in the existing literature. Therefore, the main motivation of

E. Guldogan (✉) · M. Gabbouj
Department of Signal Processing, Tampere University of Technology, P.O. Box 553, 3310 Tampere, Finland
e-mail: esin.guldogan@tut.fi

M. Gabbouj
e-mail: moncef.gabbouj@tut.fi

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this study is to widen the background knowledge on CBIR users and their hardware platforms.

System profiling is the baseline of this study as a step towards obtaining a complete set of CBIR parameters. System profiling is the process of acquiring knowledge about the hardware system of CBIR application users in order to provide enhanced services, adapt to specific requirements, and eventually improve the overall performance. This study does not consider user types in terms of their knowledge nor assumes any specific content of image databases. System profiling adapts CBIR applications to the specific hardware requirements of the system. In this study, we propose to use survey questionnaire method in order to define systems, specifications, and requirements. With this method, demands of users from CBIR applications and technical hardware specifications are determined.

We propose a definition of system profiles and efficient CBIR parameters for each specified profile in order to have acceptable semantic performance with minimum computational complexity. Semantic performance in this study refers to the level of meaningful results of a retrieval process perceived by human. One of the best criteria to evaluate CBIR performance is user satisfaction, which is proportional to the overall performance of a system. We evaluated the semantic retrieval performance of the proposed parameters by an objective evaluation technique (to be described later) from the literature. The main objectives of this study are

- Tuning and defining CBIR application features and parameters for optimal overall performance (combination of semantic performance and complexity) in each hardware platform having different capabilities, capacities, and conditions, and
- Improving the hardware scalability of the CBIR application.

The rest of the paper is organized as follows. The online survey and outcomes are presented in Sect. 2. The same section also presents analysis of the survey results. Technical specifications of the system profiles and the proposed CBIR parameters are given in Sect. 3. Comparative and detailed experimental studies are presented in Sect. 4. Finally, Sect. 5 presents the concluding remarks, discussions and future work.

2 System profiling based-on hardware specifications

2.1 Review of literature

Survey questionnaire methods have been widely used in several studies for a long time [8–11]. Especially, systems involving user interactivity utilize survey methods for usability studies [8]. CBIR applications have also been the subject of several surveys. Jaimes [10] studied human factors, which influence automatic content-based retrieval systems, such as human memory, context and subjectivity. Eakins et al. [11] used online questionnaire method in order to improve user interface of CBIR applications. Halvey and Keane in [12], studied log statistics of YouTube to provide an analysis of user's interaction with video search engines. Catarci et al. in [13] studied questionnaire-based approach to gather the user requirements for digital libraries.

Interviews and interactive observations are commonly used approaches for analyzing the CBIR users. Kirk et al. in [14] utilized interview and field observation methods to study the activities of digital image users activities such as searching and browsing digital images. Frohlich et al. in [15] used interview and observation approach in order to understand the strengths and weaknesses of past and present technology of photo sharing. Rodden and Wood in [16] used interviews and questionnaires to find out how people organize and browse their digital photo collections and how these practices will compare to those they use at present, for their non-digital collections. In their conclusions, they claimed that CBIR would need to give more meaningful results to satisfy users, for example by providing face recognition. In this study, we have also utilized interviewing and observation method for preparing the online questionnaire. The questionnaire and analysis methodologies are explained in the next sections.

User profiling has been utilized in various research domains in the literature. Kuniavsky in [17] gives answers for the questions "find out who your customers are, what they want and what they need". Indeed, it is the starting point of designing and adapting a system according to the user's requirements. Kuniavsky also explains the user profiling approach in the book and he expresses the importance of questionnaires for the profiling process in general. Weiss et al. in [18] studied user-profile based personalization in order to select and recommend content with respect to user's interest for automated online video or TV services. Vallet et al. in [19] presented personalized multimedia management systems with the capability to filter user preferences on the semantic context of ongoing user activities based on an ontology-driven representation of semantics involved in retrieval actions and preferences. In this paper, user system profiling is a distinctive aspect from the personalized user profiling systems, where they consider user's knowledge and preferences to improve the retrieval accuracy. In this study, user system profiles represent the hardware architecture, technical capabilities and conditions of the CBIR user. We consider different technical hardware specifications of the users and improve the overall performance of the CBIR application, including retrieval accuracy and run-time efficiency for each determined profile. Therefore, user system profiling constructs the baseline of this study and it is defined by analyzing the user survey results.

2.2 Questionnaire and methodology

Survey questionnaires have to be simply structured and carefully expressed to accomplish the purpose for which the survey is being conducted. Surveys are effective ways to collect information about users' needs and choices and to identify the problem areas. They give users time to think about questions, and their main advantage is their low cost.

The main goals of the survey in this study are identifying real-world problems and specifying system requirements and system limitations. When preparing the survey questions for this study the scientific strategy described in [20] is followed.

Survey questions are generated as a draft and interactively tested with four people. Direct observation approach using "think-aloud" protocol is employed for structuring the survey. The participants were observed during their first encounter with the questions, and they were encouraged to articulate their thoughts and opinions during the questionnaire. The improved survey is further assessed with ten more people to obtain the final version for publishing. After the corrections and modifications, the online survey questionnaire is distributed by e-mail. In the online survey, audiences answer the questions exactly what is being asked by selecting them from the pre-defined lists. The choices in the lists are defined during the interactive test survey described above.

The survey includes 38 questions organized in three categories in order to collect general information about the use of digital multimedia, the use of CBIR applications, and the use of CBIR features. Finally, the responses are collected and further analyzed in the paper.

2.3 Purpose of the system profiling study

Figure 1 shows the overview of the system profiling study, where indexing and retrieval factors/parameters and system profiles will be defined in the paper. A general CBIR application includes various indexing and retrieval factors and parameters that should be tuned for each hardware platform to utilize the application efficiently. Analysis of the online survey results plays an important role in determining the system profiles and selecting suitable indexing and retrieval factors and parameters.

Scalability of an application is not only the ability of functioning properly with large data but also utilizing the advantages of the modified environment efficiently. For example, a software application would be scalable if it could be ported to a new platform that has larger technical capacities and take full advantage of the larger system in terms of performance (user response time etc.). The relation between scalability and adaptability is quite close as described in [6]. In this respect, adaptation of the factors and parameters partially helps to improve hardware scalability of the application. The selection of appropriate factors and parameters is principally aimed to efficiently use the overall capacity of each system profile in order to maximize CBIR performance.

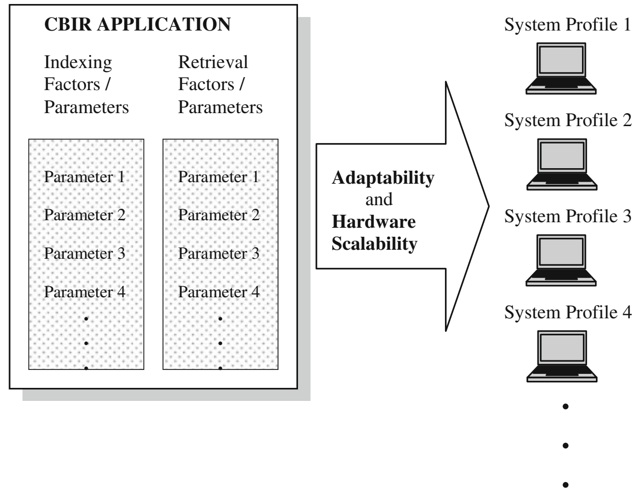

Fig. 1 System profiling for CBIR applications

2.4 Survey participants

In this study, we mainly focus on platforms utilized by end-users of CBIR applications. Thus, the target audience for the survey was selected to include both expert and non-expert CBIR users. 122 people contributed to the online survey, 27 females and 95 males participated. These include students, researchers, engineers, and professors from computer science, software systems, electronics, telecommunication, and information technology. Their age distribution is as follows: 32% are 20–24 years old, 61% are 25–35 years old, and 7% of 36–50 years old.

2.5 Evaluation and findings

In this study, we employed heuristic methodology to interpret the results of the online survey. The study revealed distinct informative knowledge about the hardware specification of the users and their preferences about digital image management. The analysis method of the survey results can be classified into two categories: direct answers from the question results and heuristic analysis of the relevant and associated survey questions. The system profiling study is based on an empirical approach using the latter method. The direct-answer method is employed for definitions and specifications of indexing and retrieval parameters for each profile.

Returning to the aim of the study, we provide answers to the definition of the system profiles in terms of hardware specifications and technical specifications affecting CBIR parameters and adaptations. The system profiles are defined heuristically based-on various answers from the online survey. The whole survey results are considered for the heuristic definitions of the system profiles. However, the most critical parameters, which have considerable impacts on the definitions, are given below for each system profile.

The profile definition is initiated with Baseline System profile, which represents the hardware specifications of an ordinary CBIR user, who does not have particular strict requirements or high expectations from CBIR applications.

Limited System Profile is constructed based on the results of 1st, 3rd, 6th, 7th, 8th, 12th and 27th questions of the survey.[1] The definition of the profile can be summarized using the following parameters:

$U_{\mathrm{LSP}} = \left\{ \begin{array}{l} \text{use of limited devices} \\ \text{use of thumbnail images} \\ \text{use of compression} \end{array} \right\}$, where U_{LSP} represents the limited system profile definition.

The information about the use of limited devices can be acquired from the first, third, sixth, seventh, and eighth questions of the survey. For example, in the first question results, 98% of the audiences are using mobile phones in their daily life, which can be considered as significant majority. Use of thumbnail images and compression can be analyzed with 12th and 27th questions of the survey, where 64% of the audiences prefer to browse image databases in thumbnail size.

Similarly, distributed system profile is created for the users, who have noteworthy rate in the answers of 18th, 24th, 26th, and 27th questions. The following parameters are considered for the definition of distributed system profile:

$U_{\mathrm{DSP}} = \left\{ \begin{array}{l} \text{use of web-based systems} \\ \text{for browsing} \\ \text{use of web-based systems} \\ \text{for searching} \end{array} \right\}$, where U_{DSP} represents the distributed system profile definition.

The information about the use of web-based systems can be obtained from 18th, 24th, and 27th questions of the survey, i.e., in 24th question, 81% of the audiences use web-based image search engines.

Finally, powerful system profile (PSP) is defined to represent users, who have the highest technical capacities, and expectations from CBIR applications (4th, 8th, 12th, 13th, 14th, 15th, 31st, and 34th questions in the survey) with the following parameters:

$U_{\mathrm{PSP}} = \left\{ \begin{array}{l} \text{use of large image collections} \\ \text{use of high quality images for CBIR} \\ \text{high expectations from CBIR systems} \end{array} \right\}$,
where U_{PSP} represents the PSP definition.

The information about the use of large image collections and high-quality images can be obtained from 4th, 12th, 13th, 14th, and 15th questions of the survey, i.e., in 12th question, 30% of the audiences prefer to see full-size images and in 15th question, 60% of the audiences do not prefer to use image compression. High expectations of relatively small group of users also have impact on the definition of the PSP, such as in 34th question; 30% of the audiences prefer high speed instead of high accuracy and in 13th question and 22% of them prefer to use high image resolutions for browsing tasks.

Moreover, each of the answers of the survey questions helps in the selection of factors and parameters and experimental case setup. For example, the answers of the 16th question in the survey reveal that 93% of the participants prefer to use JPEG image compression technique. Thus, we decide to use JPEG compressed images in the experiments.

Figure 2a to d represent selected samples from online survey results. The first example in Figure 2a represents the importance of CBIR applications, since 55% of the participants prefer to organize their multimedia files by events and people (46% by events and 9% by people), which may be extracted from the "content" of the image. The second chart in Fig. 2b helps us determine the storage space specification of the profiles, where we do not consider external storage spaces for image databases and utilize only hard drives of the concerned devices. Figure 2c reveals information about the approximate size of the image databases for the experimental studies. Finally, the fourth sample in Fig. 2d illustrates the need of unsupervised CBIR applications for managing personal image databases.

Answers of the participants for the questions of the survey are considered to define the requirements, capacities, and conditions of the systems. The defined requirements, capacities, and conditions further help to determine the parameters of indexing and retrieval factors and system profiles. The defined system profiles are explained in details in the following section.

3 System profiles and specifications

Defining the system profiles is a key issue for improving efficiency of CBIR on several platforms in terms of complexity, time and semantic retrieval performance. CBIR applications should be scalable in order to run efficiently on different user hardware systems. In this study, we define system profiles based on survey results. Especially, user needs and requirements are considered while defining the system profiles. Users' preferences may be diverse depending on their CBIR applications and hardware platforms. For example, in 27th question, 56% of the users expect instantaneous response from a retrieval system when the data and the CBIR application are locally stored and running on a personal computer. On the other hand, in 26th question, this

[1] Please see Appendix for the complete list of survey questions and results.

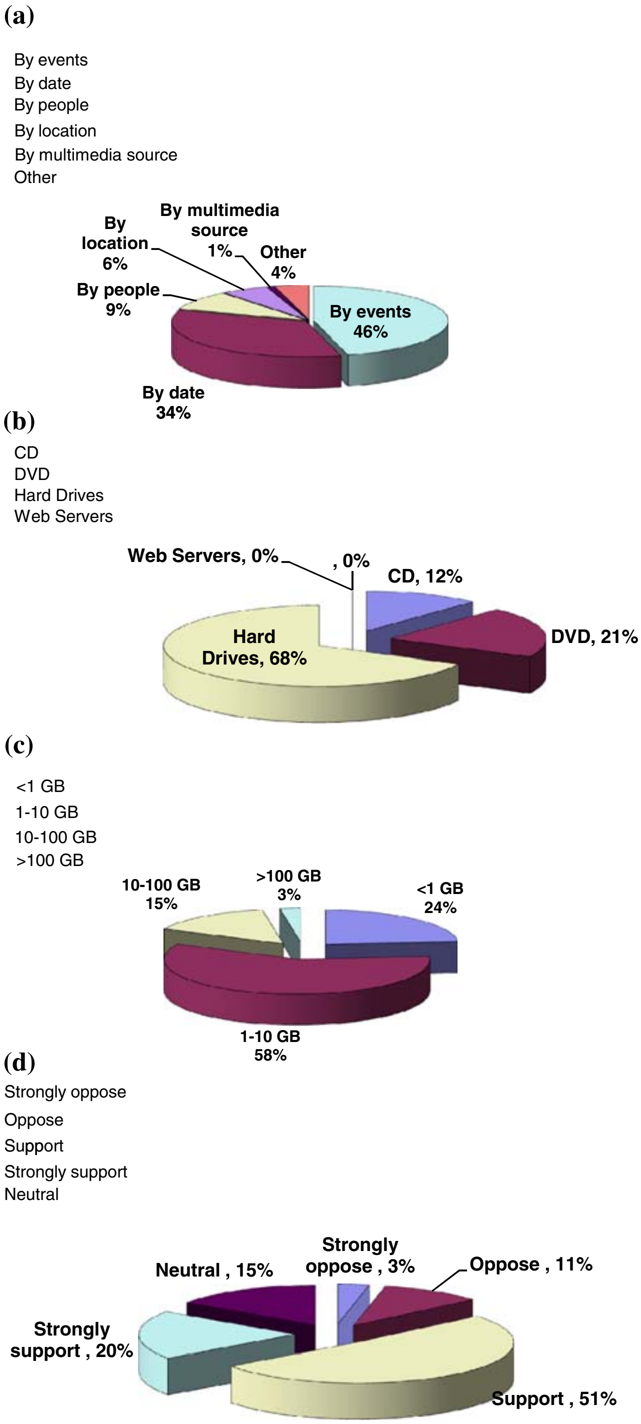

Fig. 2 Sample survey results illustrations. **a** How would you prefer to organize your multimedia files? **b** Which of the following do you prefer to use for storing your multimedia files? **c** What is the approximate size of your digital multimedia files? **d** How would an automatic search mechanism contribute in managing/handling your image database/collection?

percentage drops to 40%, when a web-based CBIR application is in use.

In this paper, we define four main groups of CBIR systems: limited, distributed, baseline and powerful system profiles. The Limited System Profile represents limited platforms such as mobile phones. Systems having client-server architecture, such as web-based systems, are represented by the Distributed System Profile. General PC and laptop users are potential users of the Baseline System Profile. Most of CBIR users belong to this profile. Powerful system profiles represents the powerful computer systems such as dedicated servers for professional use. Usually, professional users utilize such systems for CBIR, for example, TV broadcast and mass media companies and libraries.

After defining the system profiles, their technical attributes are further specified in order to identify capacities of the systems. The technical attributes of the systems defined in Table 1, have potential impact on CBIR use and the overall performance. While defining the CBIR parameters for Distributed System Profile, network connection bandwidth has to be considered due to the data traffic between client and server, where data are expected to be transferred effectively in a short time interval. Multimedia codecs and storage space capacity attributes of the existing hardware system help specifying limitations of image databases to be used. CPU processing power is one of the main factors to determine indexing and retrieval time. Finally, display size plays an important role in the interaction between CBIR applications and users. It will also increase the usability of the system, which increases the satisfaction from the system. Table 1 is obtained according to the existing technologies in last quarter of 2007.

Considering the technical attributes given in Table 1 and relevant CBIR processes, CBIR parameters factors and parameters[2] can be divided into the following two categories to ease the adaptation of the parameters for each system profile:

- Indexing factors/parameters:
  - Compression parameters
  - Scaling parameters
  - Feature type
- Retrieval factors/parameters:
  - Dimension reduction of feature data parameters
  - Feature selection

These two categories are further split into sub-groups taking into account CBIR challenges and existing prior art. The indexing process includes feature extraction and database editing sub-processes. Consequently, the challenges presented by the indexing process may be divided into three main groups: run-time memory consumption, run-time

[2] Factors in this context may also refer to specific parameters when appropriate.

Table 1 Technical features of each SP

System profiles	Limited systems	Distributed systems	Baseline systems	Powerful systems
Attributes				
Connection bandwidth	114–723 Kb/s	128 Kb/s–1 Mb/s	128 Kb/s–2 Mb/s	1–100 Mb/s
Storage space	160 MB–8 GB	10–20 GB client	∼100 GB	over 500 GB
CPU power	[Information not available]	1–2 GHz	∼2 GHz	∼2×3.0 GHz +
Display size	176×208 to 320×240	1,280×1,024	1,280×1,024	1,280×1,024 +
Multimedia codecs	Encoding: H263, MPEG4, AMR, AAC, JPEG Decoding: H263, MPEG4, AMR, AAC, MP3, JPEG2000, JPEG	Generally All	Generally All	Generally All

computational complexity, and storage space requirement. The main indexing parameters are the quality factor used in the JPEG image compression, the scaling factor of the image downscaling, while the indexing factors include the feature types. In this respect, image compression may be used to reduce the storage space and memory consumption. Additionally, image downscaling may be utilized to decrease the run-time of the feature extraction process complexity and the storage space requirement. The feature type factor also affects the run-time of the feature extraction process complexity. For example, extracting shape-based features is often computationally more complex than extracting color-based features.

Retrieval factors include similarity measurement and sorting processes. The main factors controlling the response time of a retrieval process are run-time memory consumption and computational complexity. In this respect, two main factors are considered for the retrieval process: dimension reduction of feature data and feature selection. First, a dimension reduction method reduces the feature data size; and consequently they reduce proportionally the elapsed time of the retrieval process. Second, the feature selection process refers to the process of selecting the most important features and their combinations for describing images in the database in order to reduce the computational complexity while maintaining the retrieval performance.

Table 2 is constructed according to the aforementioned categories of CBIR factors and parameters. The degree of image compression can be adjusted by the quality factor defined in JPEG for allowing a selectable tradeoff between the storage size and the image quality. Image downscaling represents the process of scaling the image down to a smaller size by a scaling factor, the so-called image downscaling parameter in this paper. The range of each CBIR parameter is specified based on the technical attributes given in Table 1 and the analysis of the survey results. The tradeoff between semantic retrieval accuracy and elapsed times for indexing and retrieval process with various CBIR parameters are considered for the final selection of the parameters on each profile. The reasons and experimental results of the parameters are given in the following section. The recommended CBIR factors and parameters for each system profile are assessed for validation.

4 Experimental studies

Several experimental studies are accomplished in order to assess the validity of the proposed system profiles and CBIR parameters. The main goal of the experimental studies is to verify that the proposed indexing and retrieval parameters for each system profile satisfy the user in terms of semantic retrieval performance and reduction of computational complexity. The parameters given in Table 2 are evaluated and compared for complexity and semantic performance analysis.

Experimental databases are constructed according to the parameters proposed above. Several experiments have been performed in this study in order to verify the proposed CBIR parameters and assess the advantages in terms of computational complexity and semantic retrieval performance.

Table 2 Recommended CBIR factors and parameters for each system profile

System profiles	Limited systems	Distributed systems	Baseline systems	Powerful systems
Indexing factors/parameters				
Compression parameters (JPEG quality factor)	Compression quality factor 50%	Compression quality factor 75–50%	Compression quality factor 75%	None or compression quality factor 90%
Image downscaling parameters	Image scaling Factor (ISC) = 4 for color features	Image scaling factor = 4 for Color features	Image scaling Factor = 2 for color features	Image scaling Factor = 2 or or none for color features
	ISC = 2 for texture and shape features	ISC = 2 for texture and shape features	None for texture and shape features	None for texture and shape features
Feature factors	Use a feature selection method	Use a feature selection method	Optionally use a feature selection method	Optionally use a feature selection method
Retrieval factors/parameters				
Dimension reduction of feature data parameters	Scaling factor = 4 or 8	Scaling factor = 4	Scaling factor = 2	None or scaling factor = 2
Feature selection and combination parameters	Use a feature selection method	Use a feature selection method	Optionally use a feature selection method	Optionally use a feature selection method

4.1 Experimental framework, queries and data set

MUVIS content-based indexing and retrieval system is utilized as the experimental framework [1]. MUVIS is a content-based indexing, browsing, and retrieval system, which supports various multimedia types such as digital images and audio/video clips. MUVIS provides three applications each having different responsibilities and functionalities:

- AVDatabase: It is a real-time audio/video database creator, which is capable of grabbing data from any peripheral device connected to a computer.
- DbsEditor: It manages the indexing and any editing tasks on MUVIS databases.
- MBrowser: It is the main application for browsing and retrieving the multimedia items.

MUVIS manages feature extraction in terms of explicit modules. Feature extraction algorithms can be implemented independently as modules, and then integrated into MUVIS framework via a specific interface called Feature Extraction Interface (FeX API). More details on dynamic integration of explicit feature extraction algorithms into MUVIS framework can be found in [21].

In the MUVIS framework, features are represented in vector forms, whereas similarity distances between the query item and members of the database are calculated to obtain a similarity distance per image using available visual features. The similarity measurements are handled in the independent feature extraction modules and differ according to the feature types. As an example, color histogram feature modules utilize Euclidean distance as similarity criterion. The query results are obtained by ranking the items according to their similarity distance to the query item over the entire database individually for each feature. Ranked distances are then merged to obtain final retrieval results for multiple queries.

Uncompressed Corel database with 10,000 images in [22] that are pre-assigned by a group of human observers to 100 semantic categories each containing 100 images is utilized for experimental studies. Some examples of the categories are autumn, balloon, bird, dog, eagle, sunset, and tiger.

The experimental database properties and the CBIR parameters are selected by analyzing the online survey results and the existing studies in the literature. The specifications of indexing and retrieval parameters for each system profile are given in Table 2.

4.2 Visual features

14 types of color, texture and shape features are utilized in all experimental studies. Color Histogram is the most commonly used color feature representation. It can be computed by

counting the number of pixels of each of the given set of color ranges so-called bins. Before building the histogram, the color space of the source is usually converted into a perceptually uniform color space, such as HSV (Hue-Saturation-Value) color space. In this study we utilize YUV, RGB, and HSV color histograms with 128, 64, and 16 bins [23]. Besides the color histogram, several feature representations based on color have been applied in multimedia retrieval, including Dominant Color [24]. We have used Dominant Color feature with three colors in the experiments. We also utilize two texture-based features. Co-occurrence matrix is one of the statistical texture features, which estimates the visual texture properties based on orientation and distances between pixels and summarizes them into meaningful statistics. Visual texture properties may be energy, entropy, contrast, etc. Gray Level Co-Occurrence Matrix texture feature with parameters 12 and 6 [25] are used in this paper. The second texture-based feature is Gabor Wavelet texture feature [26], which is a group of wavelets capturing energy at a specific frequency and a specific direction. Gabor Wavelets capture local features/energy of the signal and texture features can be extracted from this group of energy distributions. In these experiments, Canny Edge Histogram [27] is also employed. Edge histogram descriptor represents edge distribution with a histogram based on local edge distribution in an image.

4.3 Evaluation measurement

Computational complexity is measured by the elapsed times for indexing and retrieval processes on different platforms. The platforms used in the experiments and their configurations are given in Table 3.

In order to evaluate the semantic retrieval performance, average normalized modified retrieval rank (ANMRR) criterion is used [28,29]. ANMRR is defined in MPEG-7 as a retrieval performance criterion for each query (q). It considers precision, recall, and ranking information as given in the following formulas:

$$\mathrm{AVR}(q) = \frac{\sum_{k=1}^{N(q)} R(k)}{N(q)} \quad \text{and} \quad W = 2N(q) \tag{1}$$

$$\mathrm{NMRR}(q) = \frac{2\mathrm{AVR}(q) - N(q) - 1}{2W - N(q) + 1} \leq 1 \tag{2}$$

$$\mathrm{ANMRR} = \frac{\sum_{q=1}^{Q} \mathrm{NMRR}(q)}{Q} \leq 1 \tag{3}$$

where $N(q)$ is the number of relevant (via ground truth) images in a set of Q retrieval experiments. $R(k)$ is the rank of the kth relevant retrieved item within a window W and q is the query.

The best retrieval performance can be achieved when NMRR(q)=0. It can be seen from Eqs .(1) and (2) that ANMRR value decreases if ranks of the retrieved relevant images are low. Note that, a low rank means early retrieval in time. On the other hand, in the worst case, when NMRR(q)=1, none of the relevant items can be retrieved among W retrieved items. Thus, lower *NMRR* values represent successful retrieval results for the query q. The average NMRR (ANMRR) can be used as a semantic retrieval performance criterion, if the amount of query by example (QBE) experiments is high enough.

4.4 Image compression

According to the results of the online survey, JPEG compression technique is selected for image compression. Corel database is compressed with JPEG quality factors 90, 75, and 50 for different experiments on several platforms. Eight compressed and/or downscaled test databases are created from the uncompressed Corel database. The effects of compression on CBIR system semantic performance have been studied in [30,31]. As shown in [30,31], the proposed quality factors for image compressions are the minimum compression parameters, which do not affect the retrieval accuracy significantly.

4.5 Image downscaling

Image downscaling parameters are selected according to our previous studies in [32,33]. DCT-based image downscaling effects on image retrieval performance were analyzed and it was concluded that color feature based retrieval performance is not affected significantly. On the other hand, retrieval performance based on texture and shape features suffers significantly as a result of image downscaling. The proposed image downscaling parameters for color, texture, and shape features have also been tested and compared with original size image databases to quantify these effects in the experiments in this paper.

4.6 Feature selection

Feature selection process affects both indexing and retrieval complexities as well as the semantic retrieval performance. In this study, we use mutual information for feature selection, which is a widely used method in various research fields such as genomic data analysis, classification of network data, categorization of medical data, speech recognition [34–38]. The feature selection technique based on mutual information (a criterion that measures the amount of information shared between features of the query image and images in the database) and decision mechanisms developed in [38] is used for experimental studies in this paper.

Table 3 Technical features of sample SP utilized in the experiments

System profiles / Attributes	Limited systems	Distributed systems	Baseline systems	Powerful systems
				
Connection bandwidth	128/512 Kb/s	128 Kb/s–1 Mb/s	128 Kb/s–2 Mb/s	1–100 Mb/s
Storage space	1 GB	60 GB client	120 GB	180 GB
CPU power	[Information not available]	Intel Pentium 4 2.8 GHz	Intel Pentium 4 2.8 GHz	2×2.8 GHz
Display size	320 × 240	1,280 × 1,024	1,280 × 1,024	1,280 × 1,024
Multimedia codecs	MPEG-4 , H.264/AVC , H.263/3GPP, MP3-, AAC-, eAAC- and eAAC	Generally all	Generally all	Generally all

Table 4 Experimental results of image compression parameters

Image compression parameters	ANMRR results	Size on disk	Recommended system profiles
Uncompressed	0.20	2.6 GB	Powerful system profile
JPEG compressed with quality factor 90%	0.20	400 MB	Powerful system profile
JPEG compressed with quality factor 75%	0.23	310 MB	Baseline system profile and Distributed system profile
JPEG compressed with quality factor 50%	0.23	190 MB	Limited system profile

4.7 Dimension reduction of feature data

Dimension reduction of feature data process is a commonly applied method for reducing retrieval process complexity [39]. Mapping by adaptive threshold (MAT) is used for color-based features in this study since it has been shown that it does not affect color-based retrieval performance [39]. On the other hand, dimension reduction is not applied to texture and shape features, since the corresponding feature data sizes are comparatively much smaller than those of color features.

4.8 Semantic evaluation of the proposed CBIR parameters

Experiments are performed on each sample system given in Table 3, using the recommended CBIR parameters in order to assess their performance.

Table 4 shows the retrieval performances in ANMRR values and sizes of the uncompressed and JPEG compressed image databases in bytes. Note that, in the experiments $N(q)$ value is equal to 30. It is evident from Table 4 that, JPEG compression with quality factor 90% does not affect the retrieval accuracy, although it saves 85% of the storage space. Since the retrieval accuracy is not significantly affected with this compression scheme, the compressed databases are employed in the system profiles according to their sizes. Each compressed database is used as a base database for a system profile as given in Table 4 for further experiments on CBIR parameters.

In the following set of experiments, we shall assess the accuracy and run-time complexity of the proposed system profiles as exemplified in Table 3 in order to quantify the time savings and semantic retrieval results achieved by each of these profiles.

4.8.1 Powerful system profile

The configuration given in Table 3 for Powerful System Profiles (PSP) is used for the experiments. The PSP represents specific systems, which make use of dedicated servers and professional software applications. However, we have used a powerful personal computer to run these experiments to evaluate the semantic results of the proposed CBIR parameters. The semantic retrieval results are evaluated using ANMRR values as explained earlier.

JPEG compressed image database with quality factor 90% is selected as the base database for PSP as shown in Table 4.

Table 5 Experimental results of image downscaling parameter in the PSP

Image downscaling parameters	ANMRR	Elapsed times for feature extraction process on PSP
Compressed image database with JPEG quality factor 90%		
Color-based scaled by 2 and texture and shape-based none	**0.20**	**2.5 h**
Color, texture and shape-based scaled by 2	0.21	1 h
Color-based scaled by 4 and texture and shape-based scaled by 2	0.23	50 min
Color, texture and shape-based scaled by 4	0.27	18 min

Table 6 Experimental results of dimension reduction of feature data parameter in the PSP

Dimension reduction of feature data parameters	ANMRR	Elapsed times for retrieval process on PSP
Compressed image database with JPEG quality factor 90% AND images are downscaled for feature extraction process		
None	0.20	9 s
Scaled by 2	**0.16**	**5 s**
Scaled by 4	0.19	3 s
Scaled by 8	0.20	1 s

Images are further downscaled by various scaling rates. Several combinations of experiments are performed to show the semantic retrieval results and benefits of downscaling on indexing complexity and corresponding results are given in Table 5. The elapsed time for the feature extraction process is the time required to extract the features from the original size and the downscaled images.

Extracting color-based features from JPEG compressed with quality factor 90% and downscaled database, and extracting texture- and shape-based features from only compressed database gives successful retrieval results with acceptable indexing time on PSP. This image downscaling parameter is selected as the base parameter for PSP. Afterwards, MAT dimension reduction technique is applied to the feature data used in the experiments shown in Table 5 and the results of the experiments with the reduced size feature data given in Table 6. Table 6 shows the ANMRR results of the various scaling factors of MAT method and their retrieval times on Powerful System. MAT dimension reduction method enhances the semantic retrieval results due to its natural impact on histogram-based features. The method thresholds the irrelevant details and emphasizes the higher peaks on histograms such as dominant colors in color histograms. More details about the method and its semantic retrieval results can be found in the previous studies [39].

The query times with downscaled feature data are given in Table 6 in order to emphasize the benefits of the proposed CBIR parameters on the computational complexity of the retrieval process. Reducing the size of the feature data gives improved semantic retrieval results and decreases the elapsed time by 45% on retrieval process. Consequently, it is inferred from the experiments that the proposed CBIR parameter configurations for PSP achieve satisfactory semantic performance.

4.8.2 Baseline system profile

The baseline system profile represents the hardware system of a typical CBIR user, who while searching and browsing an image database, does not have particular strict requirements or high expectations from the system. In this study, we employed a personal computer, which has the configuration as given in Table 3.

Table 4 shows that the retrieval performances of the uncompressed database and the JPEG compressed database with quality factor 75%, where ANMRR values are only by 3% degraded due to compression. JPEG compressed image database with quality factor 75% is selected as the base database and DCT-based image downscaling is applied prior to extracting features, which are presented in Table 7. Image downscaling may enhance the edges between two objects having different colors in the image due to high-frequency component loss. Additionally, downscaling may also have filtering effects on the color information due to smoothing the colors. Therefore, these effects may cause slight (by 2–3%) increase in retrieval performance. As shown in Table 7, the ANMRR values increase by 3% due to the influence of image downscaling on color features, which is explained further in [32].

The resulting feature data dimension is reduced using MAT method by 2, 4, and 8 in order to assess the effects of

Table 7 Experimental results of image downscaling parameter in the BSP

Image downscaling parameters	ANMRR	Elapsed times for feature extraction process on BSP
Compressed image database with JPEG 75%		
Color-based scaled by 2 and texture and shape-based none	**0.20**	**6 h**
Color, texture and shape-based scaled by 2	0.23	1.5 h
Color-based scaled by 4 and texture and shape-based scaled by 2	0.25	1.2 h
Color, texture and shape-based scaled by 4	0.30	25 min

Table 8 Experimental results of dimension reduction of feature data parameter in the BSP

Dimension reduction of feature data parameters	ANMRR	Elapsed times for retrieval process on BSP
Compressed image database with JPEG quality factor 75% AND images are Downscaled for feature extraction process		
None	0.23	12 s
Scaled by 2	0.19	7 s
Scaled by 4	**0.19**	**4 s**
Scaled by 8	0.23	2 s

the scaling parameters, and the corresponding results are presented in Table 8. The dimension reduction method improves the semantic retrieval results as explained in Sect. 4.8.1. It also reduces 66% of the run-time retrieval complexity as shown in Table 8. Consequently, the proposed CBIR parameters achieve a successful semantic performance, with feasible processing times for the baseline system profile.

4.8.3 Distributed system profile

The Distributed System Profile is a general system profile based on a client and server architecture. The online survey results reveal that web-based distributed systems are used widely among CBIR users. In these experiments, a personal computer was used as server and a laptop computer is used as client, for which the corresponding configurations are given in Table 3. Database indexing process is performed at the server side while retrieval is handled at the client side of the distributed system.

The ANMRR results of the JPEG compressed databases with quality factor 75% show that the proposed compression parameters affect the semantic retrieval performance only by 3%, while reducing the required storage space by approximately 88% as given in Table 4. Therefore, the JPEG compressed image database with quality factor 75% is selected as the base database for further image downscaling process. DCT-based downscaled database with various scaling factors are indexed using all features and the corresponding retrieval results are given in Table 9. The retrieval results are not influenced considerably with downscaling by 2 and it has acceptable indexing process time. Hence, it is selected as the base image downscaling parameter for distributed system profile.

MAT-based dimension reduction technique is performed on the feature data extracted from the image database compressed with 75% quality factor and DCT-based downscaled by 2. As shown in Table 10, reducing the dimension of the feature data by 2 and 4 yields a similar semantic retrieval performance in terms of ANMRR values which are improved compared to the values obtained with the original size feature data. The reasons are already explained for this improvement in the Sect. 4.8.1. Due to its successful semantic retrieval results and lower elapsed times for retrieval process, scale factor four is proposed for the Distributed System profile. Note that although the same hardware system is used for the Baseline System Profile and the client of the Distributed System Profile in the experiments, the retrieval process times are higher in the Distributed System Profile due to the client-server communication overhead.

Feature selection can be employed in the Distributed and Limited System Profile in order to reduce the computational complexity of retrieval process as discussed in Sect. 4.6. The feature selection method is applied to the feature data, which are extracted from the compressed (with 75% quality factor) and downscaled database (by factor 2) that is further processed with MAT dimension reduction (using scale factor 4). Table 11 presents the retrieval results and elapsed times for retrieval task using all the features and a subset of the selected features obtained by feature selection process on the image database created using the proposed parameters.

Table 9 Experimental results of image downscaling parameter in the DSP

Image downscaling parameters	ANMRR	Elapsed times for feature extraction process on DSP
Compressed image database with JPEG quality factor 75%		
Color-based scaled by 2 and texture and shape-based none	0.20	6 h
Color, texture and shape-based scaled by 2	**0.23**	**1.5 h**
Color-based scaled by 4 and texture and shape-based scaled by 2	0.25	1.2 h
Color, texture and shape-based scaled by 4	0.30	25 min

Table 10 Experimental results of dimension reduction of feature data parameter in the DSP

Dimension reduction of feature data parameters	ANMRR	Elapsed times for retrieval process on DSP
Compressed image database with JPEG quality factor 75% AND images are downscaled for feature extraction process		
None	0.23	100 s
Scaled by 2	0.21	50 s
Scaled by 4	**0.21**	**25 s**
Scaled by 8	0.25	13 s

Table 11 Experimental results of feature selection parameter in the DSP

Feature selection parameters	ANMRR	Elapsed times for retrieval process on DSP
Compressed image database with JPEG quality factor 75% AND images are downscaled for features are scaled with MAT method		
Using all features	**0.21**	**25 s**
Using selected features	0.34	22 s

It can be inferred from the table that the feature selection process degrades the semantic retrieval results significantly. Consequently, the proposed CBIR parameters lead to a successful semantic performance for the Distributed System profile using all features.

4.8.4 Limited system profile

The limited system profile is proposed for CBIR users whose platforms are handheld devices, such as palms and mobile phones. In the experimental studies, a mobile phone with the specifications given in Table 3 was used with Mobile MUVIS content-based multimedia indexing and retrieval system, which is designed for mobile platforms running a Symbian-based operating system [40]. The proposed CBIR system parameters are defined according to the capacities of current devices; however, users may prefer changing the parameters depending on the hardware platforms.

The performance of the JPEG compressed image database with quality factor 50% is affected only by 3% due to compression as given in Table 4. Table 4 also shows that compressing the image database with JPEG quality factor 50%, achieves 92% compression ratio on the size of the database. Therefore, it is selected as the base database for the Limited System profile for applying DCT-based downscaling with factors 2, 4, and 8. Table 12 shows that texture and shape-based features extracted from the former database (downscaled by 2) yields better semantic performance than those extracted from downscaled by 4. On the other hand, color-based retrieval results are not affected considerably by DCT-based downscaling; thus they are extracted from a downscaled image database by a factor of 4 in order to reduce the feature extraction complexity by 80% as shown in Table 12.

MAT-based dimension reduction technique is performed on the feature data extracted from the image database compressed with 50% quality factor and DCT-based downscaled. As given in Table 13, reducing the dimension of the feature data by 4 yields a satisfactory semantic retrieval performance in terms of ANMRR values, which are slightly improved compared to the values obtained with the original size feature data. The reasons for this improvement are described in

Table 12 Experimental results of image downscaling parameter in the LSP

Image downscaling parameters	ANMRR	Elapsed times for feature extraction process on LSP
Compressed image database with JPEG quality factor 50%		
Color-based scaled by 2 and texture and shape-based none	0.22	∼65 h
Color, texture and shape-based scaled by 2	0.24	24 h
Color-based scaled by 4 and texture and shape-based scaled by 2	**0.26**	**13 h**
Color, texture and shape-based scaled by 4	0.30	4 h

Table 13 Experimental results of dimension reduction of feature data parameter in the LSP

Dimension reduction of feature data parameters	ANMRR	Elapsed times for retrieval process on LSP
Compressed image database with JPEG Quality factor 50% AND images are downscaled for feature extraction process		
None	0.23	140 s
Scaled by 2	0.21	65 s
Scaled by 4	**0.22**	**32 s**
Scaled by 8	0.24	17 s

Table 14 Experimental results of feature selection parameter in the LSP

Feature selection parameters	ANMRR	Elapsed times for retrieval process on LSP
Compressed image database with JPEG quality factor 75% AND images are downscaled for feature extraction process AND features are scaled with MAT method		
Using all features	**0.22**	**32 s**
Using selected features	0.38	29 s

Sect. 4.8.1. Due to its successful semantic retrieval results and lower elapsed times for retrieval process, scale factor four is selected for the Limited System profile.

The feature selection method is applied to the feature data, which are extracted from the compressed and downscaled database and further processed with MAT dimension reduction (using scale factor 4). Table 14 shows the ANMRR results and elapsed times for retrieval task using all the features and a subset of the selected features obtained by feature selection process on the image database created using the proposed parameters. The proposed CBIR parameters yield a successful semantic performance for the Limited System profile using all features, as given in Table 14.

4.9 Summary of the proposed CBIR parameters for each system profile

The proposed CBIR parameters are appropriate configurations for decreasing the run-time computational complexity and the memory consumption, while maintaining the semantic retrieval performance.

Table 15 shows the proposed CBIR parameters for each system profile. The aforementioned parameters give satisfactory indexing and retrieval results on the corresponding platforms as shown in the experiments.

JPEG image compression with a quality factor 75% gives successful retrieval results and hence can be utilized in the distributed system profile, the baseline system profile, and the PSP. However, in the PSP, it may be better to use less compression (i.e. a quality factor 90%) in order to improve the retrieval performance slightly, since there are no memory and storage space constraints in such a system. Additionally, due to memory and storage space capabilities of limited systems, image databases may be compressed with quality factor 50% and still provide satisfactory retrieval results.

Color features extracted from downscaled images do not affect the CBIR retrieval results. Thus, they can be utilized on every platform. On the other hand, retrieval results using

Table 15 Proposed CBIR parameters

	Limited systems	Distributed systems	Baseline systems	Powerful systems
				
Indexing factors				
Compression parameters	Compression quality factor 50%	Compression quality factor 75%	Compression quality factor 75%	Compression quality factor 90%
Image downscaling parameters	Image Scaling Factor (ISF)=4 for color features	ISF=2 for color, texture features	ISF=2 for color color features	ISF= 2 for color features
	ISF=2 for texture and shape features		None for texture and shape features	None for texture and shape features
Feature parameters	Use a feature selection method	Use a feature selection method	None	None
Retrieval factors				
Dimension reduction of feature data parameters	Scaling factor=4	Scaling factor=4	Scaling factor=4	Scaling factor=2
Feature selection and combination parameters	Use a feature selection method	Use a feature selection method	None	None

texture and shape features are affected by image downscaling. Hence, they can be employed on platforms that have limited processing power capacities such as distributed systems and limited systems.

Dimension reduction of feature data tends to reduce the retrieval complexity similar to feature selection methods. It can be used on every platform, and it does not affect the semantic performance significantly. Feature selection methods can also be employed on every system profile; however, they may affect the retrieval performance depending on the feature selection method in use. The Baseline and the PSP have high processing power capabilities and thus do not require any feature selection methods for preserving high retrieval performance.

Distributed and limited platforms have low resources in terms of processing power, memory and storage space. Thus, the scaling factor for the feature data dimension reduction may be higher in these profiles for reducing the overall complexity.

5 Conclusions and future work

In this paper, we presented a novel study for defining CBIR system profiles and determining suitable parameters for each profile which produces substantial savings in time and computational complexities while maintaining semantic retrieval performance.

Specifying a system profile is an important factor in CBIR studies, which may help to make the system scalable and adaptable for existing hardware platforms. System profiles allow systems to answer demands of different users. CBIR applications often consist of complex processes; therefore, the underlying main factors and parameters need to be adapted according to the limitations of the platforms. In this study, appropriate CBIR parameters are proposed for each of the defined system profiles.

An online user survey is used for determining the systems of the end-users by heuristic definitions inferred from the survey results. The proposed system profiles are the PSP, the

Baseline System Profile, the Distributed System Profile, and the Limited System Profile.

CBIR parameters are handled by grouping them into two parts: the indexing, and the retrieval. Experimental studies have been conducted for each of the proposed CBIR system profile. It was shown that the proposed factors and parameters for each system profile yield satisfactory semantic retrieval performance. On the other hand, they lead to substantial gains in computational complexity and storage space requirements. The gains with regard to the retrieval process complexity are 45% for the PSP, 42% for the Baseline System Profile, 78% for the Distributed System Profile, and 78% for the Limited System Profile. It is, however, important and required to adapt CBIR applications for the Limited System Profile. Users of the latter profile may have approximately the same level of semantic performance with those of the Baseline System Profile by appropriately modifying the parameters according to the underlying hardware architecture.

The proposed CBIR parameters are appropriate configurations to improve the efficiency of CBIR applications on different hardware platforms. However, trade-offs between parameters should be considered in case modifications or adjustments are required. For example, a Limited System Profile user may utilize an uncompressed image database instead of the compressed one for better image quality; however, in this case the storage space capacity of the device should be considered for the database size.

Finally, this study may be extended and supplemented by additional experiments, especially for future CBIR applications and user platforms, which are expected to change the proposed profiles and the proposed parameters due to advances in technology. Future work may also include investigating user satisfaction for the proposed system profiles and CBIR parameters using online surveys and further analysis.

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Appendix

Online user survey on use of multimedia and CBIR

General information on audiences:

122 Persons
Female: 27 persons
Male: 95 persons
Age distributions are 32% of 20–24, 61% of 25–35, and 7% of 36–50 years old.
Profession: Computer, Software, Electronic, Telecommunication Engineers, IT students, Researchers and Professors.

First part: general information on use of digital multimedia

1- Which of the following multimedia devices do you use?
   a. Digital photo camera 85%
   b. Digital video camera 42%
   c. Personal computer 95%
   d. Mobile phone 98%
   e. Palm 10%
   f. Other 17%

2- How often do you take digital pictures?
   a. almost every day 19%
   b. once in a week 36%
   c. once in a month 36%
   d. a few times a year 16%
   e. less frequently 7%

3- Which of the following devices do you use to take pictures?
   a. Digital camera 87%
   b. Mobile phone 47%
   c. Analog camera 12%
   d. Web-cam 14%
   e. other 0%

4- What is the approximate size of your digital image database/collection?
   a. <1GB 24%
   b. 1–10 GB 58%
   c. 10–100 GB 15%
   d. >100 GB 3%

5- Which of the following do you prefer to use for storing your multimedia files?
   a. CD 12%
   b. DVD 21%
   c. Hard-drive 68%
   d. Web-servers 0%
   e. Other 0%

6- Do you take pictures with your mobile phone?
   a. Yes 61%
   b. No 39%

7- Do you take video clips with your mobile phone?
   a. Yes 41%
   b. No 59%

8- Do you prefer to store your images/videos in your mobile phone/device?
   a. Yes 31%
   b. No 69%

9- How frequently do you access your digital image database/collection?
   a. almost every day 12%
   b. once in a week 45%
   c. once in a month 32%
   d. a few times a year 8%
   e. less frequently 3%

10- How would you prefer to organize your multimedia files?
   a. by events 46%
   b. by date 34%
   c. by people 9%
   d. by location 6%
   e. by multimedia source 1%
   f. other 4%

11- Do you use any automated/advanced tools for organizing your personal multimedia files?
   a. Yes 21%
   b. No 79%

12- Which of the following do you prefer to see for each multimedia item when browsing?

a.	Full-size image	30%
b.	Thumbnail (decimated version of the image)	64%
c.	Associated textual description (caption, date, file size, etc.)	4%
d.	Other	2%

13- What is your preferred image size/resolution for browsing?

a.	Large: over 3 megapixels	22%
b.	Medium: 1–3 megapixels	46%
c.	Small: ∼1 megapixels	19%
d.	Very Small: less than 1 megapixels	13%

14- Do you prefer to use compression for your image and video files?

a.	Yes	65%
b.	No	35%

15- Which type of compression do you prefer to use for compressing your multimedia files?

a.	Lossy	40%
b.	Lossless	60%

16- Which of the following codecs do you prefer to use for compressing your image files?

a.	Jpeg	**93%**
b.	Jpeg-2000	17%
c.	Bmp	12%
d.	Gif	20%
e.	Tif	10%
f.	Other	5%
g.	None	2%

17- Which of the following codecs do you prefer to use for compressing your video files?

a.	Mpeg	34%
b.	Mpeg-2	15%
c.	Mpeg-4	34%
d.	Divx	53%
e.	H263	5%
f.	H264	11%
g.	Other	%
h.	None	7%

18- Do you use web-browsers for searching image and video files?

a.	Yes	67%
b.	No	33%

19- Which network speed do you have while using multimedia services?

a.	Fast: over 2 Megabit per s	45%
b.	Medium: 1–2 Megabit per s	35%
c.	Slow: 128–1,024 Kilobit per s	17%
d.	Very slow: less than 128 Kilobit per s	2%

Second part: use of content-based multimedia indexing and retrieval

20- If you were given the following choices, which one would you use to classify/organize your multimedia database/collection

a.	Color content	15%
b.	Object/shape content	32%
c.	Metadata (such as date, caption etc.)	61%
d.	Short text description	48%
e.	Texture content	5%
f.	Other	1%

21- Do you ever search a specific/certain multimedia item in your digital media collection?

a.	Yes	62%
b.	No	38%

22- Do you search a multimedia item resembling/similar to a reference/example multimedia item in your digital media database/collection?

a.	Yes	37%
b.	No	63%

23- How would like to search your media files?

a.	By example	28%
b.	By text	58%
c.	By sketch	8%
d.	Other	5%

24- Do you make an image/video search from the web?

a.	Yes	81%
b.	No	19%

25- How do you search an image/video from the web?

a.	By text	77%
b.	By content	18%
c.	By color	1%
d.	By texture	2%
e.	By shape	0%
f.	By example	1%
g.	Other	0%

26- How would you prefer to search an image/video from the web?

a.	By text	39%
b.	By content	39%
c.	By color	4%
d.	By texture	3%
e.	By shape	3%
f.	By example	12%
g.	Other	1%

27- Which of the following environment/system would you use to search your multimedia files?

a.	Mobile systems	3%
b.	Web-based systems	36%
c.	Personal Computer	61%
d.	Other Distributed Systems	0%
e.	Other	0%

28- Which of the following has first priority for you while searching an image/video from the database/collection?

a.	Content	73%
b.	Date	13%
c.	Size	3%
d.	Other	1%

29- How would an automatic search mechanism contribute in managing/handling your image database/collection?

a.	Strongly oppose	3%
b.	Oppose	11%
c.	Support	51%
d.	Strongly support	20%
e.	Neutral	15%

30- What is the reasonable waiting time in your opinion to see the results of an image/video search on the Internet?

a.	Instantaneous	40%
b.	approximately 30 s	48%
c.	between 30 s and 1 min	6%
d.	1–3 mins	5%
e.	more than 3 mins	1%

31- What is the reasonable waiting time in your opinion to see the results of an image/video search on your personal computer?

a.	Instantaneous	56%
b.	approximately 30 s	31%
c.	between 30 s and 1 min	7%
d.	1–3 min	5%
e.	more than 3 min	2%

32- What would you like to see as a result of an image search?

a.	A certain image that exactly matches your criteria	15%
b.	A set of relevant images ordered according to their relevancy	73%
c.	Categorization of image collection	9%
d.	Other	3%

33- Do you prefer to save your image database/collection in your webserver?

a.	Yes	41%
b.	No	59%

34- Which of the following attribute is the most critical one for an image retrieval system?

a.	High speed	30%
b.	Accurate results	70%

Third part: use of features

35- What is your knowledge about image features?

a.	Excellent	20%
b.	Good	40%
c.	Fair	27%
d.	Poor	13%

36- If you are given a retrieval system to use, would you be interested in adjusting its feature settings for each retrieval in order to potentially achieve higher accuracy?

a.	Yes	77%
b.	No	23%

37- If you are given a retrieval system to use, would you prefer it to adjust the feature settings automatically with a reasonable error margin for each retrieval?

a.	Yes	70%
b.	No	30%

38- Which of the following do you prefer for a retrieval system?

a.	Interactive retrieval system where you can influence the results on the fly or between multiple steps	72%
b.	System that does not require any interaction and running at once	28%

References

1. MUVIS: A System for Content-Based Multimedia Indexing and Retrieval in Multimedia Databases. http://muvis.cs.tut.fi/
2. Pentland, A., Picard, R.W., Sclaroff, S.: Photobook: tools for content based manipulation of image databases. In: Proceedings of SPIE Storage and Retrieval for Image and Video Databases *II* (1994)
3. Chang, S.F., Chen, W., Meng, J., Sundaram, H., Zhong, D.: VideoQ: an Automated Content Based Video Search System Using Visual Cues. In: Proceedings of ACM Multimedia, Seattle (1997)
4. Datta, R., Joshi, D., Li, J., Wang, J.Z.: Image Retrieval: Ideas, Influences, and Trends of the New Age. In: ACM Computing Surveys, vol. 40(2) (2008)
5. Zhang, Z., Guo, Z., Faloutsos, C., Xing, E.P., Pan, J.-Y.: On the Scalability and Adaptability for Multimodal Retrieval and Annotation. In: Proceedings of 14th International Conference on Image Analysis and Processing Workshops, ICIAPW 2007, pp. 39–44 (2007)
6. Ross, A.M., Rhodes, D.H., Hastings, D.E.: Defining changeability: Reconciling flexibility, adaptability, scalability, modifiability, and robustness for maintaining system lifecycle value. J. Syst. Eng. **11**(3), 246–262 (2008)
7. ImagEval Webpage. http://www.imageval.org/
8. Covey, D.T.: Usage and usability assessment: library practices and concerns. In: Digital Library Federation, Council on Library and Information Resources reports. (2002), p 99
9. Smyth, B., Lam, C.P., Chen, X., Maxville, V.: Heuristics for image retrieval using spatial configurations. In: Proceedings of Digital Image Computing: Techniques and Applications, DICTA 2003, Sydney, pp. 909–918 (2003)
10. Jaimes, A.: Human Factors in Automatic Image Retrieval System Design and Evaluation. In: Proceedings of SPIE, Volume: 6061, Internet Imaging VII, San Jose, USA, January 2006
11. Eakins, J.P., Briggs, P., Burford, B.: "Image Retrieval Interfaces: A User Perspective", Third International Conference on Image and Video Retrieval, CIVR 2004, Proceedings of Lecture Notes in Computer Science 3115, Dublin, Ireland, 21–23 July 2004, pp. 628–637 (2004)
12. Halvey, M.J., Keane, M.T.: Analysis of online video search and sharing. In: 18th ACM Conference on Hypertext and Hypermedia, Manchester, UK, 2007, pp. 217–226
13. Catarci, T., Kimani, S., Panizzi, E., Antona, M.: Digital Library Requirements: a Questionnaire-based Study. In: In Proceedings of the 1st Italian Research Conference on Digital Library Management Systems, IRCDL 2005, DELOS Network of Excellence, January 2005, pp. 65–74
14. Kirk, D., Sellen, A., Rother, C., Wood, K.: Understanding photowork, Conference on Human Factors in Computing Systems, Canada, pp. 761–770 (2006)
15. Frohlich, D., Kuchinsky, A., Pering, C., Don, A., Ariss, S.: Requirements for Photoware. In: Proceedings of the 2002 ACM Conference on Computer Supported Cooperative Work, New Orleans, Louisiana, USA, pp. 166–175 (2002)
16. Rodden, K., Wood, K.R.: How do People manage their Digital Photographs? In: Proceedings of the Conference on Human Factors and Computing Systems (CHI 2003), ACM Press, Fort Lauderdale, April 2003, pp. 409–416 (2003)
17. Kuniavsky, M.: Observing the User Experience: A Practitioner's Guide to User Research, 560 p, pp. 129–155. Morgan Kaufmann, Menlo Park (2003)
18. Weiß, D., Scheuerer, J., Wenleder, M., Erk, A., Gülbahar, M., Linnhoff-Popien, C.: A user profile-based personalization system for digital multimedia content. In: Proceedings of The 3rd International Conference On Digital Interactive Media In Entertainment and Arts, DIMEA '08, Athens, Greece, September, 2008, vol. 349, pp. 281–288
19. Vallet, D., Castells, P., Fernández, M., Mylonas, Ph., Avrithis, Y.: Personalized content retrieval in context using ontological knowledge. In: IEEE Transactions on Circuits and Systems for Video Technology, vol. 17(3), pp. 336–346 (2007)
20. Czaja, R., Blair, J.: Designing surveys: a guide to decisions and procedures, 2nd edn, 300 p. Sage, London (2005)
21. Guldogan, O., Guldogan, E., Kiranyaz, S., Caglar, K., Gabbouj, M.: Dynamic Integration of Explicit Feature Extraction Algorithms into MUVIS Framework. In: Proceedings of the FINSIG 2003, Finnish Signal Processing Symposium, Tampere, Finland, (2003)
22. Corel Stock Photo Library, Ontario, Canada. http://www.corel.com/
23. Swain, M.J., Ballard, D.H.: Color Indexing. Int. J. Comput. Vis. **7**(1), 11–32 (1991)
24. Manjunath, B.S., Ohm, J.-R., Vasudevan, V.V., Yamada, A.: Color and texture descriptors. IEEE Trans. Circuits Syst. Video Technol. **11**(6), 703–715 (2001)
25. Partio, M., Cramariuc, B., Gabbouj, M., Visa, A.: Rock Texture retrieval using gray level co-occurrence matrix. In: Proceedings of 5th Nordic Signal Processing Symposium (2002)
26. Ma, W.Y., Manjunath, B.: Texture features for browsing and retrieval of image data. IEEE Trans. Pattern Anal. Machine Intell. **18**, 837–842 (1996)

27. Canny, J.: A computational approach to edge detection. IEEE Trans. Pattern Anal. Machine Intell. **8**(6), 679–698 (1986)
28. Vinod, V.V. (ed.): Description of Core Experiments for MPEG-7 color/texture descriptors. ISO/IEC JTC1/SC29/WG11 (MPEG) document no. N2929 (1999)
29. Manjunath, B.S., Salembier, P., Sikora, T.: Introduction to MPEG-7. Wiley, San Francisco (2002)
30. Guldogan, E., Guldogan, O., Kiranyaz, S., Caglar, K., Gabbouj, M.: Compression effects on color and texture based multimedia indexing and retrieval. In: Proceedings of IEEE International Conference on Image Processing, ICIP 2003, Barcelona, Spain, 14–17 September 2003. 2, pp. 9–12, (2003)
31. Maeder, A.J.: Lossy compression effects on digital image matching. In: Proceedings of 14th International Conference on Pattern Recognition, Australia, vol. 2, pp. 1626–1629 (1998)
32. Guldogan, E., Guldogan, O., Gabbouj, M.: DCT-based downscaling effects on color and texture-based image retrieval. In: Proceedings of the EWIMT 2004, IEE European Workshop on the Integration of Knowledge, Semantics and Digital Media Technology, London, U.K., November 2004, pp. 79–86 (2004)
33. Guldogan, E., Guldogan, O., Gabbouj, M.: Efficient image retrieval with JPEG 2000 and DWT-based downscaling. In: Proceedings of the International Workshop on Spectral Methods and Multirate Signal Processing, SMMSP 2006, Florence, Italy, 2–3 September (2006)
34. Xing, E.P., Jordan, M.I., Karp, R.M.: Feature selection for high-dimensional genomic microarray data. In: Proceedings of the Eighteenth International Conference on Machine Learning, pp. 601–608 (2001)
35. Liu, H., Yu, L.: Toward integrating feature selection algorithms for classification and clustering. IEEE Trans. Knowl. Data Eng. **17**(4), 491–502 (2005)
36. Jain, A., Zongker, D.: Feature selection: evaluation, application, and small sample performance. IEEE Trans.N Pattern Anal. Machine Intell. **19**(2), 153–158 (1997)
37. Koller, D., Sahami, M.: Toward optimal feature selection. In: Proceedings of the 13th International Conference on Machine Learning, pp. 284–292 (1996)
38. Peng, H., Long, F., Ding, C.: Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy. IEEE Trans. Pattern Anal. Machine Intell. **27**(8), 1226–1238 (2005)
39. Guldogan, E., Gabbouj, M.: Mapping by adaptive threshold method for dimension reduction of content-based indexing and retrieval features. In: Proceedings of EUSIPCO 2005, European Signal Processing Conference, Antalya, Turkey, p. 4 (2005)
40. Guldogan, O., Gabbouj, M.: Content-based image indexing and retrieval framework on symbian based mobile platform. In: Proceedings of 13. European Signal Processing Conference, EUSIPCO, Antalya, Turkey, 4–8 September (2005)