Gaps in content-based image retrieval

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ABSTRACT

Content-based image retrieval (CBIR) is a promising technology to enrich the core functionality of picture archiving and communication systems (PACS). CBIR has a potentially strong impact in diagnostics, research, and education. Research successes that are increasingly reported in the scientific literature, however, have not made significant inroads as medical CBIR applications incorporated into routine clinical medicine or medical research. The cause is often attributed without sufficient analytical reasoning to the inability of these applications in overcoming the "semantic gap". The semantic gap divides the high-level scene analysis of humans from the low-level pixel analysis of computers.

In this paper, we suggest a more systematic and comprehensive view on the concept of gaps in medical CBIR research. In particular, we define a total of 13 gaps that address the image content and features, as well as the system performance and usability. In addition to these gaps, we identify 6 system characteristics that impact CBIR applicability and performance. The framework we have created can be used *a posteriori* to compare medical CBIR systems and approaches for specific biomedical image domains and goals and *a priori* during the design phase of a medical CBIR application. To illustrate the *a posteriori* use of our conceptual system, we apply it, initially, to the classification of three medical CBIR implementations: the content-based PACS approach (cbPACS), the medical GNU image finding tool (medGIFT), and the image retrieval in medical applications (IRMA) project. We show that systematic analysis of gaps provides detailed insight in system comparison and helps to direct future research.

Keywords: Content-Based Image Retrieval (CBIR), Picture Archiving and Communication Systems (PACS), Information System Integration, Radiology, Data Mining, Information Retrieval, Semantic Gap

1. INTRODUCTION

Content-based image retrieval (CBIR) is a novel technology that describes methods and means to access pictures by reference image patterns rather than alphanumerical indices [1]. Using various visual query mechanisms, such as the query-by-example (QBE) paradigm [2], the user presents a sample image, image region of interest (ROI), or pattern to the system, which responds images similar to the given pattern. In order to allow a rapid response, discriminant numerical features that serve as identifying signatures are extracted from each image in the repository. The images are then indexed on these precomputed signatures. At query time, the signature extracted from the query example is compared with these.

Although this approach was originally developed for multimedia repositories such as the Word Wide Web, techniques for content-based access to medical image repositories are a subject of high interest in recent research, and remarkable efforts have been reported [3, 4, 5]. In particular, CBIR for picture archiving and communication systems (PACS) discussed in [6, 7, 8] can make a significant positive impact to health informatics and health care. In spite of the reports of innovations, however, routine use of CBIR in PACS has not yet been established. The reasons are manifold, but these

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are identified only informally without an objective measure for evaluating the CBIR systems and identifying the shortcomings (or gaps) in the methods.

In general, two gaps have been identified in CBIR techniques: (i) there is the *semantic* gap [1,5] between the low-level features that are automatically extracted by machine and the high-level concepts of human vision and image understanding; and (ii) Smeulders et al. have defined a *sensory gap* between the object in the world and the information in a (computational) description derived from a recording of that scene [1]. However, in our view, there are many other gaps that hinder the use of CBIR techniques in daily routine of medical image management. For instance, there is a gap between the publication of system approaches or technological concepts and their prototypical realization and implementation. As another example, there is a gap if three-dimensional (3D) image data is represented by signatures that are based on two-dimensional (2D) slices of the data.

By means of the concept of gaps, this paper presents a systematic analysis of required system features and properties. The paper classifies some prominent CBIR approaches in an effort to spur a more systematic and comprehensive view on the concept of gaps in medical CBIR research. The paper also attempts to show how the established terminology is applied to characterize and distinguish prominent medical CBIR approaches that have been published in the literature.

2. METHODS

There are several gaps that one can define to explain the discrepancy between the proliferation of CBIR systems in the literature and the lack of their use in daily routine in the departments of diagnostic radiology at healthcare institutions. It is insufficient, however, to merely define these gaps. In order to benefit from the concept of gaps, it is imperative to analyze systems presented in the literature on their capability to close or minimize these gaps. In addition to the gaps, it is also important to be aware of other system characteristics that, although not resulting in a gap, might be critical for CBIR system analysis and classification. In this section, we address these points systematically.

2.1. Defining an Ontology

We aim at defining a classification scheme by means of individual criteria, i.e., the so-called gaps. According to Lehmann [9], such ontology must satisfy several requirements regarding the entities (gaps), the catalog (ontology), and the applications of the ontology.

2.1.1. Requirements for the entities

Any ontology is an abstract complex of terms, and concrete criteria for requirements of the entities must be defined on a meta-level of abstraction. In particular, such terms must be

- *abstract*: they are formulated in a general manner that allows their instantiation to any approach of medical CBIR system that has been published in the literature.
- *applicable*: they are formulated in such a way that they can be used in a variety of semantic contexts of medicine, where CBIR systems are applied. In particular, the instantiation of the entities of the ontology should not be affected by the person using the ontology.
- *verifiable*: they are formulated in such a way that there exists a method to evaluate each individual criterion.

2.1.2. Requirements for the catalog

A system of abstract, applicable and verifiable entities is called ontology. However, in addition to the characteristics that are required for the entities of the ontology, the ontology itself must satisfy certain criteria. In particular, the collection of criteria must be

- *complete*: the ontology covers all characteristics of medical CBIR systems and can be mapped to any situation and context of use. In particular, if two systems are characterized by the instances of the entities of the ontology, these instances must differ for different systems.
- *unique*: the ontology is well defined. In other words, if a system is characterized by means of the ontology, the same system always results in the same set of instances.

- *sorted*: the entities of the ontology are ordered semantically. For instance, they are grouped to support their unique assignment.
- *efficient*: the application of the ontology is possible within a limited amount of time or efforts, and all criterions can be decided without additional devices or computer programs.

2.1.3. Requirements for the application

Regarding CBIR in medicine, an ontology is defined to characterize existing system approaches, or to assist the concept and design of a novel system before its implementation. Hence, there are two basic types of usage of an ontology:

- *a priori*: the ontology is used as a guideline for system design.
- *a posteriori*: the ontology is used as a catalogue of criterions for system analysis and weak point detection.

2.2. The Concept of Gaps

In this paper, we aim to build an ontology of gaps. The concept of gaps has often been used in CBIR literature, and the semantic gap is one of the prominent examples [1, 5]. As mentioned before, the semantic gap results from the similarity of images, which on the one hand is defined by a human observer in a particular context on a high level of semantics, and, on the other hand, results from computational analyses of pixel values regarding color, texture, or shape. In a more detailed view, the semantic gap addresses the content of the image and the features used for the signature. However, the lack of CBIR systems in routine radiological use also results from the performance and quality of those systems, as well as the disconnect in their design and implementations from their target users. In summary, our ontology of gaps must regard the

- *content*: the user's view of modeling and understanding images.
- *features*: the computational point of view regarding numerical features and their limitations.
- *performance*: the implementation as well as the quality of integration and evaluation.
- *usability*: the comfort of how the system can be used in routine applications.

2.3. CBIR Characteristics

In addition to the gaps, certain characteristics may apply to specify and distinguish medical CBIR systems. Since we aim at an a posteriori application of the gap ontology, we additionally characterize the

- *system*: the intention the medical CBIR approach is suggested for, and the data that is used with it.
- *I/O*: the level of input and output data that is required to communicate with the CBIR system.
- *signature*: the kind of features and distance measures applied by the system.

2.4. Evaluation

Based on the resulting scheme of gaps and system characteristics, we want to show how the ontology is applied a posteriori. For that, we selected three prominent research projects on medical CBIR:

- *cbPACS*: the content-based Picture Archiving and Communication System (cbPACS) [11],
- *medGIFT*: the medical GNU Image Finding Tool (http://www.sim.hcuge.ch/medgift) [12], and
- *IRMA*: the Image Retrieval in Medical Applications project (http://irma-project.org) [8].

3. RESULTS

Figure 1 summarizes the overall results. In total, we defined 13 entities in the four groups of gaps, and six entities in the three groups of CBIR characteristics. “xxx” denotes that the entity can be specified with additional information according to the medical context and/or system.

3.1. Content Gaps

This group of gaps addresses the modeling, understanding, and use of images from the standpoint of a user. Consequently, two gaps seem to be of relevance.

3.1.1. Semantic Gap

The similarity of images defined by a human observer in a particular context is based on a high level of semantics, which is usually addressed by assigning meaningful labels to the imaged concepts. In contrast, computational analysis of image content is based simply on pixel gray values. In our definition, the semantic gap is bridged if a relation of image structures to medical meaning is established. This gap in a system is then:

- *not addressed*: meaningful terms are not assigned to images or ROIs.
- *manual*: meaningful terms are manually assigned.
- *computer-assisted*: a semi-automatic process is used to assign meaningful terms.
- *automatic*: meaningful terms are automatically assigned.

3.1.2. Context Gap

The context in which a CBIR system can be used is usually restricted. Medical CBIR systems frequently are designed to support queries on a certain imaging modality or within a certain clinical context such as the protocol used or the diagnostics. These restriction allows the use of medical a priori knowledge of the imaging modality or context, which otherwise may be difficult to formulate so that it is computable. It may be desirable for the system to support generalized use with minimal to no user limitation. As such, to bridge the context gap, a system can be classified as one in which this characteristic is:

- *not addressed:* the system is *specific* in a certain context, and the context gap is wide.
- *limited*: restrictions apply only to the modality or to the protocol or to the diagnostics.
- *general*: no restrictions apply at all, neither to the modality nor to the protocol nor to the diagnostics.

3.2. Feature Gaps

Feature-related gaps arise from the computational point of view. The gaps correspond to the inadequacies of the chosen numerical features to characterize the image content.

3.2.1. Extraction Gap

Not all medical CBIR systems automatically extract the features. Some are based on manual indexing of images, which comes along with remarkable efforts and the potential of errors. This gap is bridged by computer-assisted or automatic feature extraction methods. Features are obtained from the input data

- *not addressed*: completely interactive or *manual*, e.g., manually outlined shapes.
- *computer-assisted*: partly interactive, e.g., shapes segmented with the “livewire” algorithm [10].
- *automatic*: non interactive.

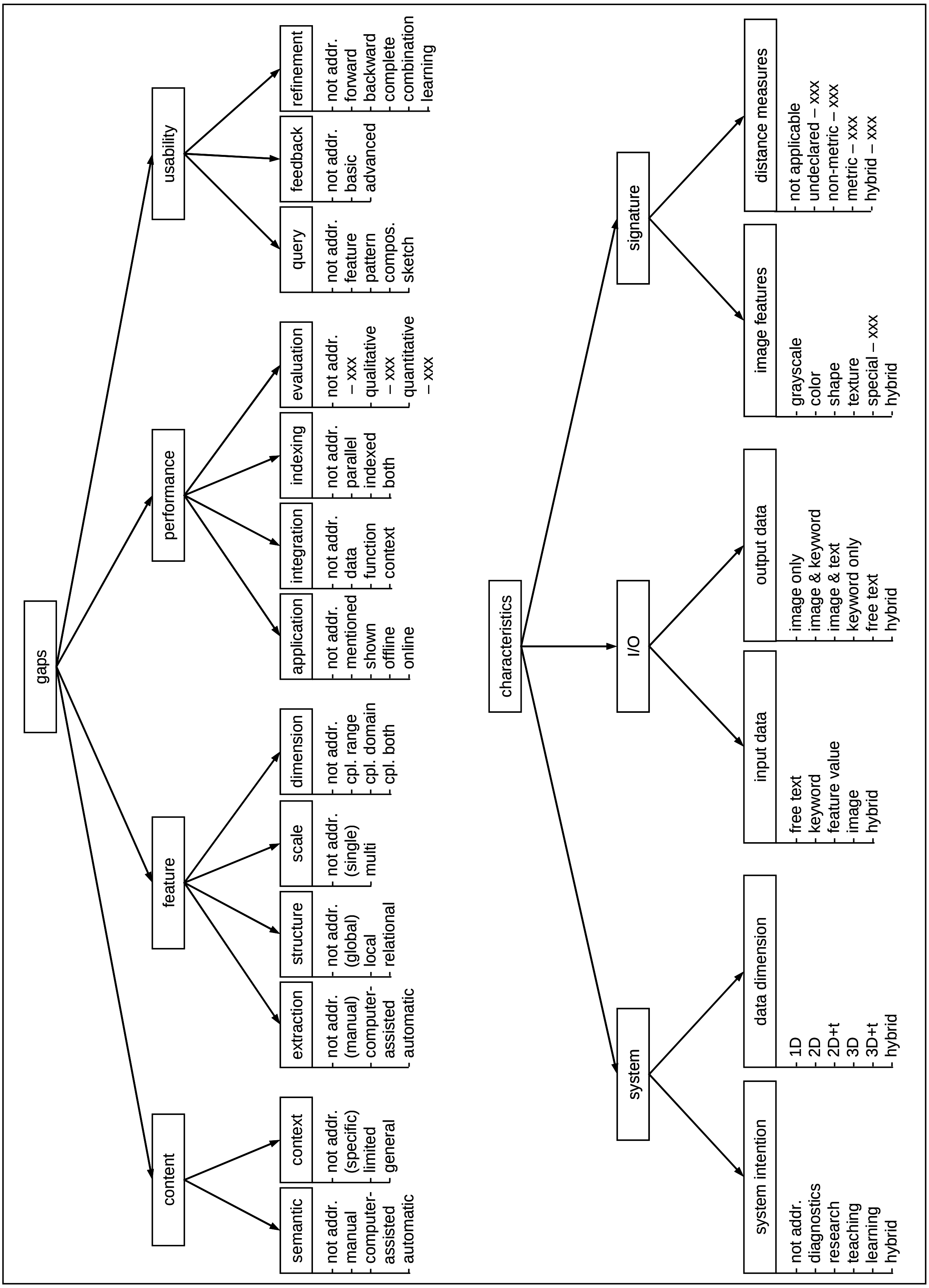

Figure 1: Results. Gaps and system characteristics in medical CBIR research.

3.2.2. Structure Gap

The extraction of global parameters which describe the entire image is frequently insufficient for medical applications. Hence, regions of interest (ROIs), which describe only a certain part of an image, must be identified and characterized by appropriate parameters. To bridge this gap, the assignment of image features is

- *not addressed*: for the entire image or *global*.
- *local*: for an individual ROI.
- *relational*: for a certain composition of individual ROIs or objects.

3.2.3. Scale Gap

Since a suitable size of ROIs or scenes again depends on the query task and context, and therefore is variable, dedicated multi-scale approaches for image content description must be developed. To bridge this gap, the scale of image analysis is

- *not addressed*: a fixed *single* scale is used.
- *multi*: a multi-scale approach is applied.

3.2.4. Dimension Gap

A system has this gap if the features are extracted and used on a dimension that is lower than the original data dimension. For instance, 3D data is processed frequently as individual 2D slices. However, for 1D biomedical signals and 2D medical images, this gap does not exist. The gap in the system is identified as:

- *not addressed*: the system handles 1D or 2D data only.
- *complete range*: for instance, color features are used for color images.
- *complete domain*: for instance, volumes are used as ROIs for 3D data.
- *complete both*: in other words, neither a domain nor a range gap opens.

3.3. Performance Gaps

Not all systems found in the literature are completely implemented and executable for performance evaluation. For those that can be tested, the performance criteria include quality of integration and evaluation in addition to other classical performance measures.

3.3.1. Application Gap

In scientific literature, there is a immense gap between the conceptual level of the described medical CBIR systems and their implementation or establishment. Frequently, concepts are published but a running system is not available. The application gap narrows if a medical CBIR application is

- *not addressed*: not mentioned at all.
- *mentioned*: in the project description, but no proof is given.
- *documented*: screen shots are shown in the publication to proof the implementation of the system.
- *offline*: available for download and installation.
- *online*: direct accessible and executable via the Internet.

3.3.2. Integration Gap

If a system for medical CBIR exists, another gap opens. Such a system usually is standalone, and not sufficiently integrated into the clinical routine. The integration gap is bridged according to the level of workflow integration. These levels are

- *not addressed*: the application is not interconnected with clinical software.

- *data*: the application can access clinical data.
- *function*: the application can be called from other clinical software.
- *context*: the actual patient/image information is passed to the CBIR application.

3.3.3. Indexing Gap

The performance of a medical CBIR system also depends on the response time and indexing of multi-scale image descriptions for efficient data access. This indexing is not trivial. Simple strategies like A*-trees or inverse files cannot be applied directly, and profound research is required to cope with large image repositories as generated in health care. The indexing gap is bridged if the computation of similarities is performed using following approaches:

- *not addressed*: the system is based on a brute force approach, where all features are compared for every image.
- *parallel*: the computation of distances is brute force but distributed.
- *indexed*: fast access to relevant feature cluster or cluster-trees is provided.
- *both*: the CBIR application employs cluster forests with distributed computation.

3.3.4. Evaluation Gap

In large data bases, the gold standard or ground truth is unknown, i.e. it is impossible to determine the correct answer for a test query. In other words, an expected output of the system answering a certain question is unavailable. Hence, the comparison of competing approaches for global/local feature extraction and distance measures is difficult and inaccurate. Instead of error measures computed from leave-one-out experiments, precision, recall, and the F-measure are calculated, where the number of correct answers is not used. Experiments are performed

- *not addressed – xxx*: no experiment are described, but the database contains xxx images.
- *qualitative – xxx*: without expected output or ground truth, based on xxx images.
- *quantitative – xxx*: with expected output, based on xxx images.

3.4. Usability Gaps

This group of gaps addresses the usability of the system. While the Performance Gaps focus on the area in which the system is used, the Usability Gaps describe the ease of use the system, from the perspective of the end user.

3.4.1. Query Gap

Using the QBE paradigm, where a visual example is presented to the retrieval system, specialized mechanisms and interfaces are required. Currently, appropriate tools to assist the user in drawing or composing a search pattern are missing, and QBE is difficult and time-consuming. The query gap in the system is identified as:

- *not addressed*: alphanumerical text is used disregarding the QBE paradigm.
- *feature*: certain intervals of feature vectors or vector components are given by the user.
- *pattern*: such a pattern can be an example image or a part of an image (ROI).
- *composition*: the user interactively selects and places structures from a given set.
- *sketch*: the system allows input of individually and interactively created pattern, including the previous options.

3.4.2. Feedback Gap

The result of a CBIR query is usually presented by displaying the most similar images found in the archive. However, it is hard to understand why the presented images are similar and how the query needs to be altered to improve the recall. To close the feedback gap, some rationale for the retrieved results is provided by the CBIR system. This can be

- *not addressed*: the results returned by the system are not commented at all.
- *basic*: a similarity number is given for each returned element.

- *advanced*: more sophisticated explanations are provided by the system.

3.4.3. Refinement Gap

CBIR systems should provide the user options to repeat and modify a query. Sometimes, they also track the refinement process to learn for user's preferences. To bridge the refinement gaps, the query refinement is

- *not addressed*: just one request is answered.
- *forward*: a rudimentary option for query refinement is provided.
- *backward*: in the refinement loop, the user can step back if results become worse.
- *complete*: a full history of the interactive session is available for restoration of any intermediate stage.
- *combination*: different queries can be performed, and their results can be combined.
- *learning*: during the usage, the system adapts to the user's need.

3.5. System Characteristics

Not all characteristics of medical CBIR systems really aim at closing a certain gap. We seek to capture these non-gap attributes, which may differ from system to system, under the general heading of system, I/O, and signature characteristics. The system characteristics address the intention of CBIR application and the data domain in use.

3.5.1. System Intention

The purpose of a system as well as the target group may vary. A medical CBIR system can assist the user in various clinical and research tasks. In particular, a system intention can be identified as:

- *not addressed*: no information about the purpose is given.
- *diagnostics*: e.g., for case-based reasoning.
- *research*: e.g., to support evidence-based medicine.
- *teaching*: e.g., for the composition of case collections.
- *learning*: e.g., the self-exploration of medical cases.
- *hybrid*: at least two of previously mentioned.

3.5.2. Data Dimension

A medical CBIR system usually copes with two-dimensional (2D) images, a sequence of images over time (2D+t), or three-dimensional (3D) volumes. The dimensionality of data that can be retrieved by the CBIR system is:

- *1D* : a biomedical signal.
- *2D*: an image.
- *2D+t*: a sequence of images.
- *3D*: a volumetric dataset.
- *3D+t*: a sequence of volumes.
- *hybrid*: more than one of the categories above.

3.6. I/O Characteristics

Content-based image retrieval in medical application may also be combined with a text-based search in the patient health record. According to Tang et al., different combinations between text and images for input and output might be used [4]. In general, it is easier to make inferences from text to images than from images to text. The first can be done from text associated with the image (e.g., Google image search), while the latter needs semantic concepts.

3.6.1. Input Data

More precisely, the system input can be:

- *free text*: any alphanumerical wording that requires stemming etc. for automatic processing.
- *keyword*: words addressing a concept of special semantics, e.g., as part of a controlled vocabulary.
- *feature value*: instances of an image-based feature, e.g., a numerical range.
- *image*: a query image, marked region of interest, drawing or any other non-alphanumeric data.
- *hybrid*: any combination.

3.6.2. Output Data

The system output can be:

- *image only*: the system returns similar images.
- *image & keyword*: similar images and controlled image category information.
- *image & text*: similar images and other text, such as in multimedia documents.
- *keyword only*: a restricted set of words based on a controlled vocabulary.
- *free text*: any alphanumerical wording that describes the image.

3.7. Signature Characteristics

The signature that is used to represent the image content is composed of numerical features and a distance or similarity measure.

3.7.1. Image Features

The type of features that are used to represent an image for content-based retrieval is an important characteristic. These features may be computed from points, lines, or areas. In particular, the image features are based on:

- *grayscale*: intensity-based features only.
- *color*: color and grayscale.
- *shape*: location or delineation of a region.
- *texture*: complex visual pattern related to a ROI.
- *special – xxx*: any context-based feature, where xxx denotes it's name.
- *hybrid*: any combination.

3.7.2. Distance Measure

Besides the type of features, different methods to determine the similarity or dissimilarity between the features must be applied. It is of special interest whether the distance measure forms a metric. According to Traina et al. [11], a distance function d(A,B), of features $A \neq B \neq C$, which is a metric, must satisfy (i) reflexivity, i.e., $d(A,A) = 0$, (ii) non-negativity, i.e., $d(A,B) > 0$, (iii) symmetry, i.e., $d(A,B) = d(B,A)$, and (iv) the triangle inequality, i.e., $d(A,B) + d(B,C) \geq d(A,C)$. In particular, the distance measure is:

- *not applicable*: no distance measure used, e.g., retrieval by intervals of feature values.
- *undeclared – xxx*: the measure is named xxx, but it is not defined whether it is metric.
- *non-metric – xxx*: non-metric distance measure is used, where xxx denotes the measure.
- *metric – xxx*: a metric distance measure named xxx is used.
- *hybrid*: any combination.

System name	Content gaps		Feature gaps			
	semantic	context	extraction	structure	scale	dimension
cbPACS	n/a	general	automatic	global	single	n/a
medGIFT	n/a	general	automatic	global	multi	n/a
IRMA concept	automatic	general	automatic	relational	multi	n/a
IRMA demo 1	n/a	limited	automatic	global	single	n/a
IRMA demo 2	n/a	limited	automatic	global	single	n/a
IRMA demo 3	n/a	specific	manual	local	single	n/a

System name	Performance gaps				Usability gaps		
	application	integration	indexing	evaluation	query	feedback	refinement
cbPACS	shown	data	indexed	qualitative – 5,549	pattern	basic	n/a
medGIFT	offline	n/a	n/a	n/a	pattern	n/a	n/a
IRMA concept	mentioned	context	parallel	qualitative	sketch	advanced	combination
IRMA demo 1	online	n/a	n/a	n/a – 9,936 stamps n/a – 5,579 paintings	pattern	n/a	n/a
IRMA demo 2	online	n/a	n/a	n/a – 10,000 x-rays	pattern	basic	combination
IRMA demo 3	online	data	indexed	n/a – 4,514 vertebrae	pattern	basic	combination

System name	System characteristics		I/O characteristics		Signature characteristics	
	system intention	data dimension	input data	output data	image features	distance measure
cbPACS	diagnostics	3D	image	image only	intensity	metric – MAM
medGIFT	n/a	2D, 2D+t	image	image only	---	---
IRMA concept	hybrid	2D	image	image & keyword	hybrid	non-metric – graph similarity
IRMA demo 1	n/a	2D	image	image only	color	metric – Euclidean RGB
IRMA demo 2	n/a	2D	image	image only	texture	non-metric – IDM, JSD
IRMA demo 3	n/a	2D	image	image only	shape	metric – Procrustes distance

Table 1: Results of a-posteriori application. MAM – histogram-based metric access method; IDM – image distortion model; JSD – Jenssen-Shannon divergence

3.8. Classification of CBIR Approaches

Table 1 shows the result of classification of cbPACS, medGIFT, and IRMA systems based on the sources [11], [12], and [8], respectively. Currently, three demo systems are available at the IRMA project home page (http://irma-project.org). In addition to the conceptual papers that have been published in scientific journals, we classified the demo systems available on the Web:

- *IRMA demo 1* – IRMA Query Demo 3.2.
- *IRMA demo 2* – IRMA Extended Query Refinement Demo 3.3.
- *IRMA demo 3* – SPIRS-IRMA Combined Retrieval.

It should be noted that medGIFT is a programming framework. As such, it allows advanced users to program their own plugins with individual features and distance measures. It is, therefore, not useful to define the distance property for it. Lack of this information is indicated with "---" in the table.

4. DISCUSSION & CONCLUSION

In this paper, we have proposed a nomenclature and classification scheme for objective assessment of medical CBIR systems. For the first time, the core features and required functionality of medical CBIR is addressed explicitly, systematically, and comprehensively. The impact of the proposed concept of gaps is shown exemplarily by analyzing three well-know medical CBIR approaches cbPACS, med GIFT, and IRMA. The variety in all columns suggests that the proposed definition of gaps and system characteristics is meaningful for system categorization and evaluation.

In addition to the gaps and system features that have been defined in our ontology, other gaps are addressed in scientific literature. For instance in the reviews of Smeulders et al. [1] and Müller et al. [5], a sensory gap is defined addressing the difference between the real world and its representation as a matrix of digital pixels. However, this problem is also exists for the radiologists looking at these digital images and therefore, we disagree with the authors in this point since we do not see the relevance of this point.

Based on this work, future research in medical CBIR can be made more effective and efficient, since the gaps that are needed to be bridged are named explicitly.

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