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RADIOGRAPHIC IMAGES DATA MODEL FOR CONTENT-BASED RETRIEVAL

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ABSTRACT

With the advance of multimedia technologies in general and diagnostic images technologies specifically, the number of radiographic images is constantly escalating in the biomedical field. This field demands sophisticated systems for management and effective search and retrieval of the radiographic images produced. This paper presents a semantic content-based radiographic image retrieval system that focuses on the semantic content of radiographic image documents to facilitate semantic-based radiographic image indexing and a retrieval system suitable for the radiographic image-on-demand style applications. The paper addresses a model developed for describing the semantic content of a radiographic image document and providing information about this content. It develops a sophisticated semantic radiographic image model that expresses the underlying semantic structure of radiographic images and retrieves content from different levels of details. The proposed semantic model is an extension of the traditional conceptual model which would be applied to the radiographic image domain. The proposed model would divide a radiographic image document, based on its semantic content, and would be converted into a logical structure or a semantic structure. The logical structure represents the overall organization of information. The semantic structure, which is bound to logical structure, is composed of semantic objects with interrelationships in the various spaces in the radiographic image.

Keywords: *Semantic Indexing, Content-Based Retrieval, Radiographic Images, Data Model*

1. INTRODUCTION

Radiographic images such as Computer Tomography (CT), Magnetic Resonance Images (MRI), X-rays, and sonograms are common ways to diagnose diseases. Many written documents are generated as interpretations for these images. With the advances of multimedia technologies in general and diagnostic images technologies specifically, the number of radiographic images is constantly increasing in the biomedical field. In this field, important information is usually conveyed in illustrations. These images provide a wealth of information related to a body's anatomy, function, symptoms, and disease associations, which is the main reason for their use. The retrieval of these images is of great importance to clinical practices, as well as education and research. Providing easy access to a database of selected teaching images would be useful to medical students and educators [21] and would improve access and retrieval of these images that may enhance decision making [10]. While the digital medical images are increasing, their effective processing is still limited. In particular, the retrieval of medical images based on their content is still difficult. Therefore, effective and efficient access to image information, based on their content, has become an important field for researchers.

Many content-based image retrieval methods were applied to medical images. Current images retrieval systems allow users to browse and explore visualized patient data, but offer little assistance in interpreting what is being displayed [25]. The semantic gap, the difference between the limited visual image features and the abundance of user semantics [29], is particularly important in medical images. Most of today's semantic retrieval of images are built on the annotation of image content. PubMed[1] and Harrison's Online[2] use keyword annotations. However, different information resources tend to use different expressions to refer to the same concept. This is referred to as a "vocabulary mismatch problem" [29]. Semantic annotation is one of the ways to narrow the semantic gap in medical images, and knowledge-

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[2] harrisons.accessmedicine.com

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driven, image content processing techniques offer promising solutions.

Domain ontology can be used as a common framework for knowledge representation and exchange because it can connect patient information to concepts stored in the knowledge base [3]. A number of projects focused on translating medical terminologies into medical domain ontologies such as UMLS[3], MeSH[4], and Radlex[5]. In addition, the semantic web community has standardized languages to represent ontologies and annotations. These are the Resource Description Framework (RDF) format for documents [1] and the Web Ontology Language (OWL) language for ontology specification [2]. The community also provided several tools for querying and performing reasoning for the knowledge base, such as such as the Protégé ontology editor[6], Jena2 Semantic Web tool kit [16], GATE for storing, indexing, and retrieving language resources in RDF[7], the sesame triplestore server which provides storage and querying capabilities of triples[8], and many other tools.

Important features in the design and implementation of the content-based retrieval system are image content extraction, representation, search and retrieval strategies, and user interface design. To date, a general and comprehensive data model for storing the semantic content of radiographic images in databases has not been developed. Once the requirements of a particular application have been determined, techniques of image analysis and description, with known database methods, are adopted to develop an image database which satisfies these requirements [19]. The content of particular images can be determined, based on the correspondence between the derived description of a particular image and some appropriate model(s) of an image class [19].

This paper introduces a structured data model to capture the semantic content of radiographic images for later retrieval. The proposed semantic model is an extension of the traditional conceptual model which will be applied to the radiographic image domain. Our objective is to index a radiographic image (annotate) at three levels of granularity: physical, semantic and logical. The logical structure represents the overall organization of information. The semantic structure, which is linked to logical structure, is composed of semantic objects with interrelationships in the radiographic image's various spaces. The semantic indexing is achieved by extracting the biomedical terms currently available in the Unified Medical Language System (UMLS) metathesaures available from the National Library of Medicine (NLM)[9], the largest biomedical domain ontology. The physical layer represents the raw data.

The paper is organized into five sections. Section 2 lists current approaches to radiographic image indexing and related works. Section 3 provides a brief definition of the semantic content-based radiographic image retrieval and states the main problems and the strategy for a solution. Section 4 describes the suggested approach towards semantic radiographic image structuring and how the model is to be organized and stored in databases. The paper is concluded and summarized in Section 5.

2. RELATED WORK

Radiographic images indexing is the continuation of ongoing research of image understanding and content-based image retrieval (CBIR) of biomedical images [5, 7, 14, 15, 18, and 22]. CBIR focuses on visual content analysis. Such systems retrieve relevant images based on visual content such as color, texture and shape. Hence, it provides query methods for images based on visual content using low-level image features.

This process, however, is facing challenges. (1) The image content is extracted using image processing techniques and standalone knowledge. (2) The low resolution, strong noise and grey level representation are common characteristics in most medical images [24]. Images may present different visual features and later generate imprecise segmentation and complexity feature extraction during the indexing process [30]. (3) Generally, the retrieval results based on the similarities of pure visual features are not necessarily perceptually and semantically meaningful and often unpredictable [24]. (4) Each type of visual feature tends to capture only one aspect of image property and it is usually hard to specify clearly how different aspects are combined [30].

[3] www.nlm.nih.gov/research/umls
[4] www.nlm.nih. gov.mesh
[5] www.rsna.org/redlex
[6] protege.stanford.edu
[7] ontoweb-lt.dfki.de/projects/gate.htm
[8] www.openrdf.org
[9] http://www.nlm.nih.gov/

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To overcome some of these challenges, some research focused on object recognition algorithms to detect particular objects in medical images [11] at the anatomical level, [27] the disease level and [8] the functional level. But these recognition algorithms are not generic.

Semantic indexing of images is another area of research. Usually semantic indexing requires the use of ontologies. Some research studies have been conducted in the area of ontology-based image retrieval, emphasizing the combination of object recognition and domain knowledge. Mechouche et al., [17] combines symbolic and sub-symbolic techniques for the annotation of brain MRIs. Vompras [28] proposes an integration of spatial context and semantic concepts into the feature extraction and retrieval process. Papadopoulosa, et al. [20], combines machine learning algorithms with spatial information using domain ontology.

Natural language processing (NLP) techniques have been applied to radiology reports to extract salient terms [23, 6, 26, and 9].

To facilitate semantic content-based retrieval of radiographic images, this paper focuses on developing a comprehensive conceptual model for describing the semantic content of a radiographic image document and relevant information about this content. The paper presents a sophisticated semantic radiographic image model that expresses the underlying semantic structure of radiographic images.

3. RETRIEVING RADIOGRAPHIC IMAGES

Radiographic images provide users with a wealth of information. This information needs to be addressed by the machines in order to facilitate retrieval. As mentioned in the previous section, much research in image processing has been devoted to understanding and analyzing the *perceptual* content of a radiographic image document, however, the *semantic* content has been ignored in the analysis. Consequently, existing content-based radiographic image retrieval systems based on processing techniques may not fully meet the needs or answer queries which are merely based on the semantic content of images. We have concluded that technologies are needed for radiographic images to support their content-based searching and retrieval and overcome the limitations of processing techniques.

Several approaches exist to determine search criteria for retrieving digital images in general. The approaches are based on media description such as type, format and compression techniques, content classification such as a user's level of expertise and disease category, subjective description, such as keywords and technical descriptions such as size, resolution and content description. In analyzing a document, end users think of ideas contained in the document rather than its title or its technical details.

To make a radiographic image searchable as text and websites, we must focus our attention on its content rather than on titles or attributes irrelevant to the content. *Content-based image retrieval* is characterized by the system's ability to retrieve an image from a collection of documents based on the content rather than on attributes irrelevant to the content.

What distinguishes one x-ray image from another is the content, but not necessarily the color histograms or edge maps. Humans tend to address an image on the basis of meanings or its semantics. During retrieval, humans seek to find information in response to spontaneous worded requests. This information tends to meet their perception of the radiographic image document's content. The new trend of radiographic images retrieval systems focus on retrieving images on the basis of semantic content, which is referred to as *semantic content-based radiographic images retrieval*.

A. Strategy of Solution

Radiographic images are a complex and unstructured type of media. A great deal of effort has been put into image retrieval, but the main question that needs to be asked is how a radiographic image retrieval system can be developed if a radiographic image document is not understood. It becomes evident here that a diverse model to represent the different aspects of the information contained is needed.

To develop a semantic content-based radiographic image retrieval system, it is necessary to follow this procedure:

- Develop a formal description for semantic radiographic image content;
- Set indexes that are efficient in terms of storage and search time, conforming to the human perspective and address as much information as possible in a radiographic image document;
- Study the capability of existing signal processors and the method of integration with the proposed

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semantic model to maximize procedures that can be automatically conducted;

▪ Develop an efficient structure for the semantic radiographic image acquisition and retrieval in light of the proposed semantic model;

▪ Design querying methods for radiographic image documents that meet human needs;

▪ Eliminating semantic and schematic heterogeneity between query content and radiographic image content.

4. SEMANTIC RADIOGRAPHIC IMAGE MODEL

At the semantic level, a radiographic image document is an *unstructured* media type. It has no underlying semantic structure. Physically, a radiographic image is a series of pixels. A fundamental task in the semantic radiographic image modeling is to identify a conceptual structure of a radiographic image document known as *radiographic image semantic structuring.*

According to Open Document Architecture [12] and Standard Generalized Markup Language (SGML) [13], a document has two conceptual structures:

- The logical structure represents the overall organization of information.
- The layout structure represents the presentation of a document on a screen or a paper which is automatically related to the logical structure

Semantic structure is a third structure proposed by this paper. The structure is bound to the logical structure and expresses the meaning of the content of the logical elements.

B. Radiographic image Conceptual Layers

To capture the radiographic image conceptual structure, a sample of user queries generated by radiologists was analyzed in the biomedical field. Some examples of the constructed queries include:

"Retrieve radiographic images of chest x-rays performed on patients over 40 years old after 1/6/2009"
"Retrieve female patients with breast cancer under 40 years old"
"Retrieve radiographic images with enlargement of the right ventricles"
"Retrieve female patients with pneumonia above 40 years who live in Saudi Arabia"
"Retrieve radiographic images of 50-year-old patients with lung cancer"
"Retrieve X-rays of chest that show Tube closes"
"Retrieve radiographic images of Stage III lung cancer"
"Retrieve radiographic images of big cysts formed behind the right knee"

With a preliminary analysis of the entire sample set, the paper proposes the following conceptual model for radiographic images. The model is composed of physical, semantic and logical layers. The semantic layer and a logical layer are built on top of the physical layer of a radiographic image to provide a semantic abstract view of the image content. Semantic content-based image retrieval does not work with the physical layer directly, but with the semantic layer and the logical layer. Layers proposed for the radiographic images are shown in Figure 1 and are described as follows:

1. *Physical layer* is the raw data which contains objects.
2. *Semantic layer* is an abstract layer in which the physical layer's contents are linked into the real world using medical ontology. It represents the meaning of those physical objects. The levels of semantic layers are referred to as intermediate and high-level.

   2.1 *Intermediate level* semantics are directly extracted from the physical layer. These are the elementary objects, perceptual features and spatial associations. This is achieved by mapping salient terms to the UMLS Metathesaues. The intermediate level can be used to answer clinical questions such as 'Find a lung'.

   2.2 *High-level* semantics are composed of intermediate level content. In the proposed semantic model, composite units, high-level descriptions and contextual associations are considered high-level semantics. Ontology knowledge representation and inference rules are needed to detect high-level semantics. High-level can be used to answer clinical questions such as 'Find Choroid plexus cyst'.

3. *Logical Layer* is composed of units, each constructed from units from the semantic layers. The logical layer is used to answer clinical questions such as, 'Find a 25-year-old male diagnosed with lung cancer'.

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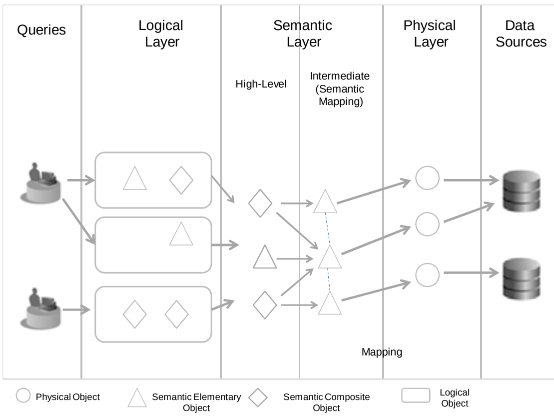

Fig 1. Radiographic image Conceptual Layers

C. The Conceptual Model

Semantic content-based radiographic image retrieval is the selection of an image from a collection of radiographic images on the basis of their content description. The first step toward developing a semantic content-based radiographic images retrieval system is the development of a formal conceptual modeling of radiographic images content description.

The proposed model is based on the consideration of the radiologist's description of a radiographic image. A user view of a radiographic images document is the perception of the proposed image's content. Understanding the user view helps decides what aspects of the radiographic images should be considered and stored. This will enable the proposed model to depict the user's various perspectives of a radiographic images document. The document will then help develop a system capable of answering the user's heterogeneous queries.

Based on the aforementioned samples of queries collected and analyzed, the user could reveal different perspectives, depending on meaningful entities and descriptions of interest that exist in a conceptual structure. In addition, semantic units in a radiographic image document are related to each other in the image space, contextual space and logical space. The user may refer to a semantic unit based on its relationship with another; e.g. radiographic images of 'cyst formed *behind* the knee versus a cyst as *part-of* the brain.

The proposed semantic model is represented by semantic units, descriptions and associations. This section focuses on the provision of an elaborate semantic model to describe the semantic content of images. The model addresses the semantic structure, the high-level semantics composition and the content indexing.

End users often have a fuzzy understanding of their own need. Fuzzy needs could be expressed with a number of possible interpretations or representations. In semantic content-based radiographic images retrieval, end users are unaware of the image structure and annotations stored. In such cases, keyword-based retrieval fails to retrieve images that are unquestionably correct semantically. End users employ various types of abstraction to construct their own view. Therefore, *abstraction* is an important mechanism for imitating the user view of radiographic image content in that it associate a physical element with a real world concept.

The content of the radiographic images is usually meaningful when associated with secondary information related to patient demographics, procedures and information provided by domain experts following the analysis of the images. This information is represented by logical structure.

As a conclusion, we use two complementary structures to represent the information related to radiographic images. These are logical and semantic structures. In radiographic images, the semantic structure is embedded in logical components.

C.1 Logical Structure

The logical structure represents the overall organization of the medical domain's radiographic information. By studying the radiographic image report documents generated by domain experts and analyzing the potential queries, the author suggested the following logical elements to represent the appropriate structure of a radiographic image.

- Patient Demography: An example would be the patient's properties such as age and gender which can be automatically extracted from the DICOM [4] headers of many images.
- Clinical Procedure: Procedure with properties modality, date, time and type which are requested by a physician, radiologist, or medical institute. The data can be automatically extracted from the DICOM headers of images.

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- Symptoms: Store the observations made including the anatomical location
- Diagnosis: Store the identification of the disease.

C.2 Semantic Structure

The proposed semantic radiographic image model is based on the human perspective in order to have a system that could retrieve clips capable of answering human query. Hence, the conceptual model based on the user view constitutes:

- Semantic units
- Associations among semantic units
- Descriptions of semantic units and associations
- Logical component
- Abstraction mechanisms over semantic units, descriptions and associations.

Semantic Units

A significant issue is the identification of the *meaningful* units (semantic units) in a radiographic image. The meaning is guided by a medical ontology used to define concepts. In our work we used UMLS as our primary medical ontology knowledge base.

A *physical object A* is an instance of a salient object captured in a radiographic image's physical space and represented visually or textually. Each physical object identified in a radiographic image is entered in the real world knowledge base. A *semantic object* is a physical object identified by the viewer in that it belongs to the medical knowledge base. In radiographic images, a *semantic object O* is linked to the physical object *A* that occurred in an image in the medical knowledge domain and is represented by *A(O).*

In the medical field, a number of objects could be related to each other. For instance, *digestive system* is a collection of related objects of class *organ*. All this leads to the concept of composite semantic units which allow the construction of new semantic units from existing ones. A *composite semantic unit* is a structure built of instances of elementary and possibly other composite semantic units which could be of heterogeneous type, with a semantic interrelationship to express a complex fact. For instance, a *Choroid plexus cyst* is a composition of *cyst part-of brain*. Figure 2 below illustrates the relationship between elementary semantic object, composite semantic objects and knowledge domain.

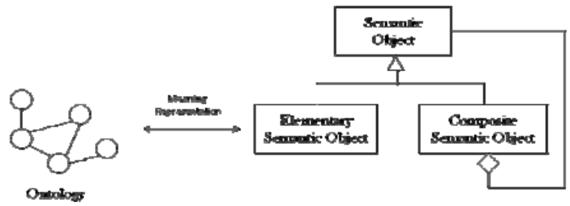

Fig. 2. Radiographic images Semantic Unit Representation

Observation Image

A semantic unit *O* may appear in a number of radiographic images. Therefore, a semantic unit is associated with a radiographic image identifier (*ID*). The observation image denoted by *T(ID, O)* links an abstract concept of a semantic unit with a physical collection of radiographic image documents.

Associations

To represent the various interactions among semantic units within a radiographic image space and the relationship between semantic units and logical elements, the concept of *association* is introduced. A key characteristic of the radiographic image is the various relationships embedded in, and connecting, semantic units.

Semantic units are interrelated in context, structure and space. This indicates three types of semantic associations: contextual, structural and spatial. Like semantic units, associations are attached with observation images.

1. *Contextual association* is an n-ary relationship between *n* semantic units in context. For instance, a contextual connection such as in ‘X *functionally related to* Y’ or ‘X *Part of* Y’ may exist between two semantic units of class *organ*. Contextual association is denoted by $R(A_1, .., A_n)$ where A_i is a semantic unit and *R* is an association name.
2. *Structural association* is a binary association between instances of semantic units in the logical structure. For instance in ‘disease’, the order of semantic units indicates a structural relationship between a *tumor* and *diagnosis*. Structural association is denoted by *R (A, B)* where *A* is a semantic unit, *B* is a logical unit and *R* is the association name, such as component-of.
3. *Spatial association* is a binary association between two semantic units indicating relationship in space, expressed qualitatively based on the order of units in space and denoted by $R(A_1, A_2)$, where $R \in$ {*above, left, in front, between* } and their inverse. For

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instance, a cyst formed *behind* the knee is a spatial association between two objects.

Description

Descriptions are important features in conceptual modeling. In the model proposed in this paper, an optional open set of content attributes is tightly related to each semantic unit and association. Modeling associations by simple semantic constraints is insufficient to express real-world relationships. Associations need to be described as well as semantic units for a more precise result.

The *description* of semantic units or associations is an open set of attributes and values representing features of interest to the end user. Descriptions can be perceptual (media-dependent) such as color or semantic (media-independent) such as gender and average size. Semantic units or associations may appear in a number of radiographic images leading to two categories of content attributes:

- *Static* attributes have fixed values such as a patient's *name* and *date of birth* and *uncontrollable growth* of disease, class of cancer and *fat content* of *Lypomas*.
- *Dynamic* attributes change their values in the observation image such as the spatial position, number and average size of a cyst.

Logical Units

A *Logical unit* is defined as a collection of semantic units, indicated by changes of values of dynamic attributes. A is a subset of (or is included in) L, denoted by $A \subseteq L$. Suppose L is a logical unit and A is a set of semantic units (activities or objects), then $a_i \subseteq l_j$ where $a_i \in A$ iff $T(a_i) \subseteq T(l_j)$. Logical units are denoted by $S(A, L)$, where there exists a structural association, S to relate A to a logical component. Logical units are formally defined as:

$\forall a_i \in A, \exists l_j \in L \wedge \exists s \in S$ where $s(a_i, l_j) \wedge T(a_i) \subseteq T(l_j)$.

Abstractions

Classification, generalization and aggregation abstractions are the common abstraction mechanisms available for grouping instances of semantic unit, description or association within classes building class hierarchies and constructing complex semantic units. Abstraction is essential for modeling real world features and associations as well as semantic units. In a semantic radiographic image model, however, abstraction should be considered for content attributes and attribute values.

1. *Classification* abstraction allows for the definition of the classes of semantic units. For instance, class of object *patient*, *gender* description of class patient and association class '*physically related to*.
2. *Generalization* abstraction allows for the definition of hierarchies of the classes of semantic units, as for instance *lung cancer* class is a subset of *lung tumor*. Let C be a set of homogeneous classes of semantic units, descriptions or associations. Generalization abstraction G is defined as a subset of C X C. Generalized concepts are organized into a hierarchy of *IS-A* relationship in which sub-classes inherit all properties of super-classes.
3. *Aggregation* abstraction is a class structuring mechanism for assembling complex semantic units, descriptions and associations from elementary or composite ones with a *component-of* relationship. For instance the object *digestive system* is an aggregation of more elementary objects such *teeth, pharynx ,and stomach.* Semantic unit aggregation is a special case of a structuring composite unit.

Definition of Semantic Units and Associations

This section shows how semantic information is stored in databases. A semantic unit or an association is a quadruple (uid, F, V, ∂) in which *uid* is the identifier, F is a set of content attributes (static attributes) and V is a set of attributes' values $V = \cup_{f \in F}$ *domain(f)*. Then ∂ maps attributes into their values $\partial : F \rightarrow V$ such that $\partial (f) \in domain(f)$.

Suppose an object *patient* with a quadruple (34, F, V, ∂) is given where:

F = {name, date-of-birth, gender, class, …} is a set of content attributes.

V = {Ali, 2-6-1972, male, patient, ...} is a set of attributes' values.

∂(name) = Ali, ∂ (date-of-birth) = 2-6-1972, ...

Definition of a State

The states of semantic units and associations are each recorded in a 9-tuple ($S, uid, T, F, V, L, \vartheta, \lambda, \ell$), where S is a set of state identifiers, *uid* is the semantic unit or association identifier in which states belong, T is a set of observation image, F is a set of dynamic attributes, V is the set of their values, ϑ maps states into a set of attributes and values such that ϑ: $S \rightarrow$ P(∂) and $\vartheta(s) \in \{ \partial_1, \partial_2, ...\}$ where $\partial_i \in \partial$, λ maps states into observation images such that λ: $S \rightarrow T$ then λ(s) $\in$ t, and ℓ maps states into set of logical elements such that ℓ: $S \rightarrow L$ and $\ell (s) \in \{ l_1, l_2, ...\}$ where $l_i \in L$ then ℓ (s) $\in$ l

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Suppose the semantic object patient with a 7-tuple (S, 123, T, F, V, L, ϑ, λ, ℓ) is given where:

S = { s_1, s_2, …} set of states of a unit.

T = { 12, 13, …} set of observation images in which an object appears.

F = {stage, size, number, X, Y, …} set of dynamic attributes.

V = { III, 20, 2, 20, 30, … } set of attributes' values.

L = {treatment, diagnosis, …} set of logical unit component.

∂_1(stage)= III, ∂_2(X) = 30, ∂_3(Y)= 20, ...

$\vartheta(S)$ maps states into attributes and attributes' values as follows:

$\vartheta(s_1) = \{ \partial_1, \partial_2 \}$, $\vartheta(s_2) = \{ \partial_3, \partial_4 \}$, ...

$\lambda(S)$ maps states into observation images as follows:

$\lambda(s_1) = 12$, $\lambda(s_2) = 13$, ...

ℓ (S) maps states into logical units as follows:

$\ell(s_1)$ = diagnosis, …

5. CONCLUSION

The objective of this work is to develop a content-based retrieval system for radiographic image documents based on their semantic content. In developing the system, it is essential to define a rich and sophisticated conceptual model insightful enough to describe the semantic content of radiographic image documents and to answer users' heterogeneous queries. This work attempts to emulate radiologists understanding of the semantic content of a radiographic image and consequently develop a formal semantic model for radiographic image content and semantic retrieval. It explains in detail the proposed semantic radiographic image model and the way this model is stored in databases. The proposed model allows associations to be defined over semantic units and logical units in order to develop high-level semantics. Another extension allows for the application of abstraction mechanisms to any type of semantic unit, description or association unlike other models which can be applied only to objects.

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