

# Efficient Method for Image Indexing in Medical Application

**Richard Chbeir**

*University of Bourgogne, France*

## INTRODUCTION

In last two decades, image retrieval has seen a growth of interests in several domains. As a result, a lot of work has been done in order to integrate it in the standard data processing environments (Rui, Huang, & Chang, 1999; Smeulders, Gevers, & Kersten, 1998; Yoshitaka & Ichikawa, 1999). To retrieve images, different methods have been proposed in the literature (Chang & Jungert, 1997; Guttman, 1984; Lin, Jagadish, & Faloutsos, 1994). These methods can be grouped into two major approaches: metadata-based and content-based approaches. The metadata-based approach uses alphanumeric attributes and traditional techniques to describe the context and/or the content of the image such as title, author name, date, and so on. The content-based approach uses image processing algorithms to extract low-level features of images such as colors, textures, and shapes. Image retrieval using these features is done by methods of similarity and hence is a non-exact matching.

The requirement of each method depends on the application domain. In this paper, we address the domain of medicine where image retrieval in particular is very complex and should consider:

- Both content-based and metadata representations of images and salient objects. This guarantees a pertinent integration of all the aspects of image in order to capture pertinent information and to assure the relevance of all query types (Chbeir, Atnafu, & Brunie, 2002).
- High-precision description of images. For example, the spatial data in surgical or radiation therapy of brain tumors is decisive because the location of a tumor has profound implications on a therapeutic decision (Chbeir, Amghar, & Flory, 2001; Chbeir et al., 2002). Furthermore, it is crucial to distinguish between similar situations. Figure 1 shows two different images of three

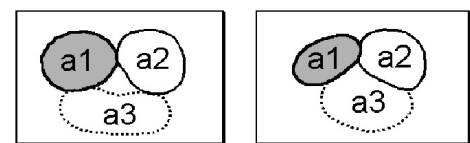
salient objects that are traditionally described by the same spatial relations in both cases: topological relations: a1 Touch a2, a1 Touch a3, a2 Touch a3; and directional relations: a1 Above a3, a2 Above a3, a1 Left a2.

- The evolutionary aspect of image content (Chbeir, Amghar, Flory, & Brunie, 2001) such as tumor development in brain (Figure 2), virus changes, and so on. The detection of the evolutionary aspects of objects (displacement, deformation, contraction, rotation, etc.) can significantly help physicians to establish an appropriate diagnosis or to make a therapeutic or surgical decision. An example for such a query is: "Find treatments of lesion detected inside brain images where a size increasing has been observed at every examination between time  $t$  and  $t+n$ ".

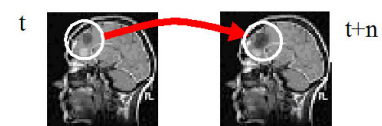
In this article, we address the spatial and evolutionary issues of images. We propose a novel method that considers different types of relations. This method allows providing a highly expressive and powerful mechanism for indexing images.

The rest of this article is organized as follows: the next section is devoted to detail the related work. In the following section, we define our method of

*Figure 1. Two different spatial situations*



*Figure 2. Tumor growth inside the brain*



computing the different relations and we show how image indexing can be done. The subsequent section demonstrates how our method can adequately index medical images. Finally, we conclude and give future work orientations.

## RELATED WORK

The problem of image retrieval is strongly related to image representation. Computing relations between either salient objects, shapes, points of interests, etc. have been widely used in image representation such as R-tree and its variants (Beckmann, 1990; Guttman, 1984), hB-tree (Lomet & Salzberg, 1990), ss-tree (White & Jain, 1996), TV-tree (Lin et al., 1994), 2D-String and its variants (Chang & Jungert, 1997; Chang & Jungert, 1991; Chang, Shi, & Yan, 1987), and so on. Spatial relations are mostly used for indexing and retrieval purposes for its automatic detection capability.

Three major types of spatial relations are generally proposed in image representation (Egenhofer, Frank, & Jackson, 1989):

- Metric relations measure the distance between salient objects (Peuquet, 1986). For instance, the metric relation “far” between two objects A and B indicates that each pair of points  $A_i$  and  $B_j$  has a distance greater than a certain value  $d$ .
- Directional relations describe the order between two salient objects according to a direction, or the localisation of salient object inside images (El-kwae & Kabuka, 1999). In the literature, fourteen directional relations are considered:
  - **Strict:** north, south, east, and west.
  - **Mixture:** north-east, north-west, south-east, and south-west.
  - **Positional:** left, right, up, down, front and behind.

Directional relations are rotation variant and there is a need to have referential base. Furthermore, directional relations do not exist in certain configurations.

- Topological relations describe the intersection and the incidence between objects. Egenhofer

and Herring (1991) have identified six basic relations: disjoint, meet, overlap, cover, contain, and equal. Topological relations present several characteristics that are exclusive to two objects (i.e., there is one and only one topological relation between two objects). Furthermore, topological relations have absolute value because of their constant existence between objects. Another interesting characteristic of topological relations is that they are transformation, translation, and scaling invariant.

In spite of all proposed work to represent complex visual situations, several shortcomings exist in the methods of spatial relation computations. Particularly, traditional methods do not have the required expressive power to distinguish between similar situations in critical domains such as in medicine.

On the other hand, the evolution of image content needs to be taken into consideration in several domains. Any evolution needs to consider time and thus temporal relations. For that reason, two paradigms are proposed in the literature in order to compute temporal relations:

- The first paradigm consists of representing the time as a set of instants:  $t_1, \dots, t_i, \dots, t_n$ . Traditionally, only three temporal relations are possible between two objects: before, its symmetric relation after, and equal.
- The second paradigm considers the time as a set of intervals  $[t_i, t_j]$ . Allen relations (Allen, 1983) are often used to represent temporal relations between intervals. Allen proposes 13 temporal relations (Figure 3), in which six are symmetrical.

For instance, in geographic applications, spatio-temporal queries (Bonhomme, Trepied, Aufaure, & Laurini, 1999) are used more and more to study the translation of a mobile object, the evolution of spatial objects, and so on. In the medical domain, images are evolutionary in nature. Their content evolution description can provide an important support for the treatment of diseases. To the best of our knowledge, the evolutionary content of medical images was only studied by Cárdenas, Jeong, Taira, Barker, and Breant, (1993); Chu, Hsu, Cárdenas et al. (1998). In Cardenas et al. (1993), the authors study the development of

6 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage: [www.igi-global.com/chapter/efficient-method-image-indexing-medical/17254](http://www.igi-global.com/chapter/efficient-method-image-indexing-medical/17254)

## Related Content

---

### Optical Flow Prediction for Blind and Non-Blind Video Error Concealment Using Deep Neural Networks

Arun Sankisa, Arjun Punjabi and Aggelos K. Katsaggelos (2019). *International Journal of Multimedia Data Engineering and Management* (pp. 27-46).

[www.irma-international.org/article/optical-flow-prediction-for-blind-and-non-blind-video-error-concealment-using-deep-neural-networks/245752](http://www.irma-international.org/article/optical-flow-prediction-for-blind-and-non-blind-video-error-concealment-using-deep-neural-networks/245752)

### Relationships between Wireless Technology Investment and Organizational Performance

Laurence Mukankusi, Jared Keengwe, Yao Amewokunu and Assion Lawson-Body (2009). *Encyclopedia of Multimedia Technology and Networking, Second Edition* (pp. 1206-1214).

[www.irma-international.org/chapter/relationships-between-wireless-technology-investment/17538](http://www.irma-international.org/chapter/relationships-between-wireless-technology-investment/17538)

### Adaptation and Personalization of Web-Based Multimedia Content

Panagiotis Germanakos and Constantinos Mourlas (2009). *Multimedia Transcoding in Mobile and Wireless Networks* (pp. 160-177).

[www.irma-international.org/chapter/adaptation-personalization-web-based-multimedia/27200](http://www.irma-international.org/chapter/adaptation-personalization-web-based-multimedia/27200)

### Young Children and Digital Media in the Home: Parents as Role Models, Gatekeepers, and Companions

Patricia Dias and Rita Brito (2018). *Digital Multimedia: Concepts, Methodologies, Tools, and Applications* (pp. 964-981).

[www.irma-international.org/chapter/young-children-and-digital-media-in-the-home/189511](http://www.irma-international.org/chapter/young-children-and-digital-media-in-the-home/189511)

### Extracting More Bandwidth Out of Twisted Pairs of Copper Wires

Leo Tan Wee Hin and R. Subramaniam (2009). *Encyclopedia of Multimedia Technology and Networking, Second Edition* (pp. 552-559).

[www.irma-international.org/chapter/extracting-more-bandwidth-out-twisted/17448](http://www.irma-international.org/chapter/extracting-more-bandwidth-out-twisted/17448)