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Medical visual information retrieval based on multi–dimensional texture modeling

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Abstract

The importance of medical visual information search and the major challenges ahead are detailed. Experiences from research activities of the eight past years at the MedGIFT group are shared and subsequent ongoing research directions are proposed to yield a flexible framework for indexing medical visual information of any dimension and any modality based on texture information.

Keywords: Content–based image retrieval, texture, information, systems, medical image analysis.

1. Introduction

The importance of medical images increases for establishing diagnoses, for teaching and treatment planning. Standardized imaging protocols allow to accurately confirm the presence of abnormalities and quantitatively evaluate their extent. The imaging techniques evolved in order to be able to assess the visual appearance of almost every organ with both high spatial and temporal resolution. Functional imaging was also more recently proposed to study the behavior of certain organs. All the specific requirements for imaging each organ bred a wide range of imaging techniques producing multidimensional data in the forms of signals, images (2D), images series (3D volumes, videos or 4D volumetric videos) and combination of modalities. As a consequence, the amount of visual information created in modern hospitals exploded in the last decade. Such a tremendous amount of visual information calls for computerized aid both at a large–scale management level of the whole content of the PACS (Picture Archiving and Communication System) [1] and at the diagnosis level for the interpretation of single image series. Furthermore, recent advances in medical informatics enabled access to most of the radiological exams to all clinicians through the electronic health record (EHR) and the PACS. This change of the medical workflow requires computer expert systems able to bring the right information to the right people at the right time.

1.1. Medical visual information search

The approach of an inexperienced clinician to a diagnosis is to compare the image under investigation with typical cases with confirmed diagnosis listed in textbooks or contained in personal collections. It allows to rule out diagnoses and, in association with clinical parameters, prevents the reader from mixing diagnoses with similar radiological findings. This process allows the clinician to partly replace a lack of experience but has two major drawbacks: searching for similar images is time–consuming and the notion of similarity may be subjective and can be ambiguous as being driven by intuition of the clinician.

A survey on health care professionals' image use and search behavior [2] showed that content–based search for images from the entire PACS to retrieve similar cases appears as very beneficial for diagnosis aid but was rarely tested in clinical practice so far [3]. Most of the clinicians are building personal image collections where search is mostly based on the patient name. Quality of image search on the Internet is hard to judge and is mostly limited to 2D images with little contextual information.

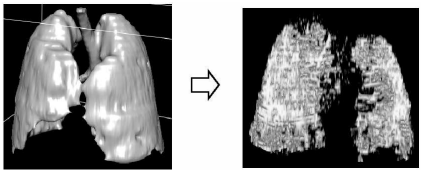

Figure 1. Use of 3D texture analysis to characterize biomedical tissue.

2. Texture modeling for indexing

Content–based medical image retrieval (CBMIR) has been a emerging research field in the past 10 years, with an increasing number of papers [4]. CBMIR aims at finding objectively visually similar images in large standardized image collections such as PACS [1]. However, the usage of CBMIR in clinical practice is still rare because it does not fulfill all clinician's needs, yet [4]. Four main reasons can be clearly identified. First, most of the proposed systems cannot handle images of more than two dimensions (e.g. IRMA[1], MedGIFT[2], ...). Second, image features are still not able to efficiently describe the users' intents, which have been identified as the semantic gap in the literature [1, 4]. Further research is needed to build flexible image features that are able to adapt to various imaging modalities in varying number of dimensions and organs. To do so, visual features must go beyond descriptions of 3D surfaces and towards 3D texture containing much richer information (see Figure 1), which was little attempted in the literature.

Organs and tissue anomalies are well characterized by localized texture properties in most imaging modalities. Imaging devices are reaching increasingly high spatial resolutions allowing to characterize structural properties of biomedical tissue. Third, clinicians are usually searching for similar cases with similar radiographic findings, but also using the clinical context such as age, gender and laboratory results. As a consequence, CBMIR systems need to be based on several images as well as clinical parameters, which was rarely described in the literature. Fourth, innovative graphical user interfaces (GUIs) need to be designed to allow for submission and retrieval of several multidimensional images from cases with enhanced visualization and navigation abilities.

[1] Image Retrieval in Medical Applications (IRMA)
[2] Medical GNU Image Finding Tool

Figure 2. GUIs for 3D lung image retrieval.

3. Results

Through the past eight years, the MedGIFT group[3] accumulated experience on case–based, texture–based indexing and GUIs for CBMIR in a close collaboration with the clinicians and radiologists at the University Hospitals of Geneva. The available experiences are reviewed in Section 3.1 and the current ongoing research is described in Section 3.2.

3.1. Available computer tools

2D affine–invariant texture feature are available and proved to efficiently describe content of high–resolution computed tomography images of the chest affected by interstitial lung diseases and could be successfully used to assess inter–case visual similarity [5]. The use of contextual clinical parameters to improve image analysis was demonstrated in [6]. Graphical user interfaces (GUIs) and clinical workflows allowing for case–based search as well as efficient querying and browsing of multimedia data were proposed in [7].

3.2. Flexible content–based indexing

A medical image analysis framework offering high flexibility and being expected to catch the specific texture signatures of most organ anomalies in most imaging modalities is currently developed in the MedGIFT group. The goal is to develop algorithms that are able to analyze new modalities with a minimum adaptation effort. During the last fifteen years, the arrival of new imaging modalities in clinical routine increased, and the replacement times of tomography stations becomes increasingly short, creating a lack of experience among all

[3] `http://medgift.hevs.ch/`

radiologists with the new modalities. Making available images from the new modalities from the start can help clinicians to better understand the subsequent potential benefits and pitfalls. In parallel, solutions for large scale computing are investigated to enable the indexation of the enormous amounts of visual data produced.

4. Conclusions

The importance of medical visual search and the current lack of maturity of the current CBMIR systems are described. The proposed research directions are expected to contribute to a common usage of CBMIR systems in clinical routine in a close future.

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