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Article Title: Review on Topical Content-Based Image Retrieval Systems in the Medical Realm

Review on Topical Content-Based Image Retrieval Systems in the Medical Realm

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ABSTRACT

Content-Based Image Retrieval (CBIR) has been one on the most vivid research areas in the field of computer vision over the decades. The availability of large and steadily growing amounts of visual and multimedia data, and the development of the Internet underline the need to create thematic access methods that are more than simple text-based queries or requests based on matching exact database fields. Content-based Image Retrieval (CBIR) aids radiologist to identify similar medical images in recalling previous cases during diagnosis. Although several algorithms have been introduced to extract the content of the medical images, the process is still a challenge due to the nature of the feature itself where most of them are extracted in low level form. In addition to the dimensionality reduction problem caused by the low-level features, current features are also insufficient to convey the semantic meaning of the images. This article gives an overview of available literature in the field of content-based access to medical image data and on the technologies used in the field. The shortcomings of the current CBIR systems are discussed and future directions toward context-based medical image retrieval are expressed.

Keywords: Image Retrieval (IR), Content-Based Image Retrieval (CBIR), Medical Image Retrieval, Machine Learning, Neural Network, and Deep Learning.

1 Introduction

In recent times, the usage of digital images is becoming more popular across different sectors including medical, scientific experiments, educational and so forth. Millions of medical digital images are utilized for therapy, diagnosing purpose across the globe. Hospitals and medical institutions are generating a great number of digital images such as x-ray, mammogram and magnetic resonance imaging (MRI) as part of their daily routine. Interpreting the medical images is certainly a complex task which requires extensive knowledge. In order to assist radiologists in interpreting the medical images, researchers have developed support systems such as Computer Aided Diagnosis (CAD) system and Content Based Image Retrieval (CBIR) system. CAD would help radiologists in diagnosis and also serve as a second opinion [1]. On the other hand, Content-based Image Retrieval (CBIR) uses visual content i.e. Color, Shape, and Texture to help users browse, search and retrieve similar medical images from a database based on the user's interest [2]. CBIR aids the user to meet his/her requirements with the finest results. The upcoming sections outline the CBIR medical system and its current techniques in medical domain.

2 Content Based Medical Image Retrieval System

Content-based image retrieval (CBIR) is a retrieval technique that focuses on the visual content of images rather than relying solely on metadata or textual information. CBIR systems extract features from images, such as color, texture, shape, or deep learning-based representations, and use these features to measure similarity and retrieve similar images. CBIR finds applications in various domains, including medical imaging, where it aids in diagnosis, research, and education by enabling efficient access to relevant medical images CBIR methods, such as feature extraction, similarity measurement, and relevance feedback, are commonly employed in medical image retrieval systems. These techniques enable medical professionals and researchers to efficiently search and retrieve images based on various criteria, including anatomical structures, pathology, and imaging modality [2-3].

The CBIR system plays a significant role in the medical domain by aiding medical professionals in the analysis, diagnosis, and research of various medical conditions. Some of the CBIR key roles in the medical field are listed below:

- Teaching and Education
- Image Similarity Comparison which involves medical image database
- Disease Diagnosis and Classification
- Examination and Clinical Decision Support
- Treatment Planning and
- Image-Guided Interventions.

Medical image databases are essential for developing clinical practise and promoting medical imaging research. For a variety of uses, they offer access to a repository of annotated medical images for academics, physicians, and educators. These databases make it possible to create and evaluate novel algorithms, validate diagnostic methods, and train machine learning models for medical image processing. Additionally, they aid collaborative studies, longitudinal analyses, and comparative studies [4]. There are numerous methods used in medical image retrieval, some of which includes Region of Interest (ROI), CBIR, Deep Learning (DL), Ontology-based Retrieval and fusion approach which does the following work: [5-8].

- Extraction of DL features from Convolutional Neural Networks (CNNs) which are frequently utilized in CBIR systems to represent the visual content of medical images.

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 119-124

- Ontologies, such as RadLex or SNOMED CT, are utilized for semantic indexing and retrieval of medical images, capturing relationships between anatomical structures, pathologies, and imaging modalities.
- ROI-based retrieval focuses on specific anatomical regions or pathologies of interest, enabling more targeted and precise retrieval results.
- Hybrid approaches combine multiple techniques, such as content-based features, metadata, and semantic information, to improve the accuracy and effectiveness of medical image retrieval.

3 Current Content Based Medical Image Retrieval Techniques

This section reveals the recent CBIR techniques which are presented to elevate the performance in the medical domain. Here, these techniques cover overall fineness in image retrieval concept. Ramalhinho et al. [9] discussed the registration approach using Content-Based Image Retrieval (CBIR) to address the challenges resides in making accurate registration of laparoscopic ultrasound (LUS) images. A set of possible LUS planes from CT images is simulated and descriptors for each image are generated. The Bayesian framework estimates the most likely sequence of CT simulations that matches a series of LUS images. The CBIR formulation includes multiple labeled objects and separates liver vessels into portal vein and hepatic vein branches, thereby improving the registration accuracy. This CBIR-based approach has the potential to enable the clinical application of image fusion techniques, facilitating the registration of LUS images with pre-operative CT images for improved guidance during laparoscopic liver resections.

Rossi et al. [10] described a supervised Siamese deep learning architecture for radiologists to overcome the challenges in diagnosing and interpreting the prostate cancer. It is specifically designed to handle multi-modal and multi-view MR images with similar PIRADS (Prostate Imaging Reporting and Data System) scores. This CBIR architecture enhances the workflow, accuracy and the performance of radiological interpretation.

Zhuang et al. [11] presented the WSAN (Weakly Supervised similarity Analysis Network, a DL network for analyzing the similarity of lung CT images and enabling effective content-based retrieval. One notable advantage of this system compared to existing deep learning-based medical image retrieval systems is its weak supervision. Unlike other approaches that require expert physicians to label the images for network training, the WSAN model eliminates this need. Despite the weakly supervised training, the WSAN-based retrieval system achieves satisfactory performance in terms of retrieval accuracy and effectiveness.

Fang et al. [12] revealed Y-Net framework tackles manifestation ambiguity in medical instance retrieval by encoding images into compact hash-codes, incorporating class-aware semantic information and spatially subtle differences of pathological regions. This framework encodes images into compact hash-codes by aggregating convolutional features. It consists of three

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branches: the main branch, the R-MAC branch, and the FPN branch. The R-MAC branch utilizes the classification loss to encode class-aware semantic information of pathological regions into the convolutional features, thereby avoiding the SPDD (Semantic Pathological Description Disorder) problem. On the other hand, the FPN branch employs pixel-wise segmentation loss to encode the spatially subtle differences of pathological regions into the convolutional features, overcoming the DPSD (Detailed Pathological Structure Description) problem. By unifying the classification and segmentation training, the convolutional features learned in the main branch are directly aggregated to generate hash-codes for similarity measurement. This Y-Net offers the advantage of delivering prompt real-time responses while significantly enhancing overall performance.

Xing et al. [13] presented multi-label proxy metric learning strategy which is capable of simultaneously performing pathology classification and content-based image retrieval. This strategy employs the multimorbidity metric learning, leveraging the benefits of proxies to effectively learn a feature vector space that captures the relationships between disease labels. The effectiveness of this strategy is noticeable in terms of classification and retrieval task performance.

Arai et al. [14] discussed the disease-oriented image embedding with pseudo-scanner standardization (DI-PSS), framework for embedding MR images, specifically designed for CBIR. This framework transforms the MR images to resemble those acquired using a predefined standard scanner and also overcome the data harmonization issue. This process reduces bias resulting from variations in scanners and scan protocols, while preserving disease-related anatomical features in a low-dimensional representation. Notably, the DI-PSS framework works perfectly even using a single set of image converters for training the model.

Agrawal et al. [15] revealed a Content-Based Medical Image Retrieval (CBMIR) system that utilizes a deep learning architecture. The precision and computational cost reduction of the system is improvised by reducing the search space via query image classification. This model achieves better 5-fold cross-validation accuracy and retrieval performance by training and distance-based measures.

4 Scrutiny of this Review

There are points to bring out the nature of the chosen CBMIR methods that have been reviewed. Each method has its own appreciable pros and negotiable cons but its performance doesn't refrain from reaching its goal.

Notable Pros:

- Ease of registration even when dealing with small space.
- Integration of all information in multi–parametric medical imaging tasks which predicts the similar images in diagonal.
- Better similarity retrieval results

International Journal of Advanced Trends in Engineering and Management (IJATEM)
pp. 119-124

- Alleviate the pathologically abnormal regions' ambiguity.
- Better accuracy, classification, and interpretability.
- Not needing complex domain prediction tasks beforehand and efficiently utilizing the vast amount of medical image data.

Cons to be conquered in future:

- Limitation in adaptation of other interventional Ultrasound guidance problems.
- Inflexible design to get into clinical practice.
- Cost of annotation when handling large medical image database.
- Need for validation and verification to pass through diverse data

5 Conclusion

This survey offer valuable insights into the principles, techniques, and applications of content-based image retrieval, both in general and within the context of medical imaging. Since the medical image retrieval is a complex and active research area, various techniques, including traditional information retrieval methods, machine learning algorithms, and deep learning approaches, are used to improve the accuracy and efficiency of retrieval systems. It's important to note that the field of medical image retrieval is continuously evolving, and researchers are actively exploring new techniques and methodologies to improve retrieval accuracy, efficiency, and usability. The choice of techniques depends on the specific requirements and available resources in a given medical imaging application. Also, sets a foundation for further exploration of CBIR methodologies and their advancements in the field.

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