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A review on multimodal medical image fusion: Compendious analysis of medical modalities, multimodal databases, fusion techniques and quality metrics

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Abstract

Background and objectives

Over the past two decades, medical imaging has been extensively apply to diagnose diseases. Medical experts continue to have difficulties for diagnosing diseases with a single modality owing to a lack of information in this domain. Image fusion may be use to merge images of specific organs with diseases from a variety of medical imaging systems. Anatomical and physiological data may be included in multi-modality image fusion, making diagnosis simpler. It is a difficult challenge to find the best multimodal medical database with fusion quality evaluation for assessing recommended image fusion methods. As a result, this article provides a complete overview of multimodal medical image fusion methodologies, databases, and quality measurements.

Methods

In this article, a compendious review of different medical imaging modalities and evaluation of related multimodal databases along with the statistical results is provided. The medical imaging modalities are organized based on radiation, visible-light imaging, microscopy, and multimodal imaging.

Results

The medical imaging acquisition is categorized into invasive or non-invasive techniques. The fusion techniques are classified into six main categories: frequency fusion, spatial fusion, decision-level fusion, deep learning, hybrid fusion, and sparse representation fusion. In addition, the associated diseases for each modality and fusion approach presented. The quality assessments fusion metrics are also encapsulated in this article.

Conclusions

This survey provides a baseline guideline to medical experts in this technical domain that may combine preoperative, intraoperative, and postoperative imaging, Multi-sensor fusion for disease detection, etc. The advantages and drawbacks of the current literature are discussed, and future insights are provided accordingly.

Introduction

For more than two decades, different medical imaging modalities have been used in clinical applications for disease diagnostic purposes. Generally, it is difficult to extract all required information from a single imaging modality to guarantee clinical precision and strength of the examination for diagnoses. Therefore, multimodal methods combine medical images from various modalities to make a new fused image with rich information that is reliable for clinical usage. Multimodal Medical Image Fusion (MMIF) utilizes images from different sources like X-Rays, Computed Tomography (CT), Single Photon Emission Computed Tomography (SPECT), Ultrasound (US), Magnetic Resonance Imaging (MRI), Infrared and Ultraviolet, Positron Emission Tomography (PET), etc. Images from MRI, X-ray, CT, and US can all show where the lesion is located, how large it is, and what it looks like, as well as the morphological and structural changes it has induced in nearby tissues. To get insight into a tumor's biological processes, soft tissue as well as functional information, the use of PET, fMRI, and SPECT is becoming more common. Functional and structural data of the medical images can be combined to produce more valuable information. Medical image fusion plays a critical part in the treatment of the same human organ, allowing for more accurate disease monitoring and analysis [1]. Image fusion techniques are widely applicable in the following domains, including remote sensing, machine learning, satellite surveillance, contrast enhancement of images, boosting geometric adjustment, and medical imaging to significantly improve features that have not been observable using a single image, such as malignancies, lesions, cancer cells, etc. [2]. The growing number of research articles available in magazines, books, and journals demonstrates the high interest and importance of multimodal image fusion. Fig. 1 displays the number of publications in the area of multimodal image fusion per year. The results were obtained from PubMed, an online database for biomedical subjects [3].

The multimodal medical image fusion techniques and classifications have been summarized in various surveys and review articles [[2], [3], [4], [5], [6]]. For instance, Alex et al. [2] cover the various scientific issues addressed in the area of medical image fusion. Define medical image fusion research by the techniques, imaging modalities, and organs examined, but the multimodal databases and fusion quality assessments metrics were still missing in this survey. Jiao et al. [4] explained multimodal medical image fusion steps, e.g. image fusion decomposition, and reconstruction, and fusion rules, in detail, comparing six fusion methods and using eight image fusion quality metrics. The work focuses exclusively on Harvard medical (AANLIB), but there is still a need to examine more multimodal databases for a greater variety of datasets. Additionally, the author did not address current diseases involved with MMIF in their research. Fatma et al. [5] introduced the classification of medical image registration and highlighted medical image fusion and the current diseases based on fusion work. Bikash et al. [6] provided a detailed comparison of region-based image fusion techniques using different fusion quality metrics. The images used in this review were from different sources, such as multimodal medical images, infrared rays, and visible image fusion, multi-focus image fusion, etc. The MMIF quality metrics are also discussed in tabular form.

Table 1 summarizes a recent literature review and compares it to our current study. We highlight many critical points that must be included in each MMIF evaluation. The table below is based on the following points:

IM (Imaging Modalities); It describes the presence of multimodal medical imaging modalities used in fusion.

Quant. A (Quantitative Analysis); whether the survey articles presented quantitative comparison on different fusion metrics for various techniques.

Qual. A (Qualitative Analysis); whether the survey articles presented qualitative comparison on different fusion imaging modalities for various techniques.

D.D (Database Description); It shows whether the review articles encapsulated multimodal databases with comprehensive descriptions that use in medical fusion.

T.D (Techniques Description); It represents whether review articles have any theoretical technique description for MMIF.

D.F (disease-based Fusion); the articles included diseased-based fusion work in their contribution or not.

F. B. S (Fusion Basic steps); whether the articles included general steps and rules to perform medical image fusion before going toward advanced techniques.

M. D. (Metrics Description); is there a proper description of MMIF performance metrics in survey articles.

We present a review of multimodal medical imaging modalities by overcoming all the shortcomings of the previous works, thoroughly discussing such modalities, freely accessible multimodal databases, classification of medical image fusion techniques, and associated diseases. The MMIF approaches are classified into six domains: spatial, frequency, decision-level fusion type, deep learning, hybrid, and sparse representation fusion. These five MMIF methods are compared with each other based on fusion quality performance metric results. In addition, some recent multimodal image fusion articles of different disease detection are also summarized. The arrangement of this review article is highlighted in Fig. 2.

The major contributions of this paper are as follows:

- Classification of medical imaging modalities based on the electromagnetic spectrum and invasive/non-invasive methods are shown in Fig. 3 and Table 2, respectively. The categorization based on the energy source used for image acquisition is presented in Fig. 4.
- The detailed comparisons of all online public accessible multimodal medical databases are presented in Table 3. The frequency distribution of the usage of each database over the last five years is shown in Fig. 6, and the articles compared in this review using each mentioned database are summarized in Fig. 6 (b).
- The overall general and basic procedure of medical image fusion techniques are presented in Fig. 11, Fig. 12.
- The classification of medical image fusion techniques based on frequency fusion, spatial fusion, decision-level fusion, deep learning, hybrid fusion, and sparse representation fusion is shown in Fig. 13.
- Comparison of visual image results obtained using various MMIF approaches implemented in this is shown in Fig. 14.
- The taxonomy of existing works based on different diseases is summarized in Table 6.
- All the possible MMIF quality assessment metrics are explained in Table 7.
- The medical image fusion statistical results of the six different methods using one large database, i.e., AANLIB, are tabulated in Table 8.

Section 2 contains a full discussion of medical modalities. Section 3 discusses open access multimodal medical databases. Section 4 discusses the method of medical image fusion and its categorization discussed in Section 5. Section 6 illustrates the diseases related to each technique. The fusion quality assessments metrics are explained in Section 7, while the review article is concluded in Section 8.

Section snippets

Medical imaging modalities

In the medical field, each imaging modality has unique information and characteristics. The different medical imaging modalities used for screening and diagnoses of different diseases of the human body lie in the entire electromagnetic (EM) spectrum range, as shown in Fig. 3. Each imaging modality has a different wavelength and frequency and also shows different characteristics [13]. When EM waves strike an object, they are scattered, reflected, or absorbed by the object. MRIs generate a …

Multimodal image databases

In this section, we discuss some important multimodal medical datasets that are a crucial initial step of any multimodal medical image fusion technique, particularly for testing and diagnoses. Although many datasets are freely available online for experimental purposes, researchers need medical images from different modalities of the same and different patients for validation of the fusion algorithm. These images are mostly acquired within the same periods, while other images are taken at …

Fusion steps

The multimodal image fusion method is a procedure that integrates many images from one or various imaging modalities to increase accuracy and quality while preserving the complementary information of the images [32]. Medical image fusion mainly concerns MRI, PET, CT, and SPECT [2]. PET and SPECT modalities deliver images with functional information of the body, such as details about metabolism, soft tissue movement, and blood flow, despite having low spatial resolution. MRI, CT, and US provide …

MMIF techniques classification

Although there are several image fusion approaches, we concentrated on six dimensions: frequency fusion, spatial fusion, decision-level fusion, deep learning, hybrid fusion, and sparse representation fusion. We begin by providing an overview of pixel-level and feature-level image fusion to aid in the comprehension of broad categorization.

In pixel-level-based fusion methods, images are combined straightforwardly utilizing singular pixels to make the fusion decision [27,37]. It further classified …

Multimodal fusion and recent diseases

MMIF has demonstrated exceptional performance for analyzing diseases and improving the precision and performance of the diagnostics area. In the medical field, the information from a single imaging modality does not provide complete information of human body organs. For example, MRI images show only soft-tissue information, while CT images display bone density information. Thus, MMIF becomes a vital zone of research because of its significance for providing high-quality output images for …

Image fusion quality assessment metrics

The quality of a fused image is determine by Fusion Quality Assessments Metrics (FQAMs) following subjective/qualitative and objective/quantitative methods. Particularly, subjective methods are based on visual examination to compare the final fused image with original input images. The examination of the fused image considers various parameters like image size, spatial details, color, etc. However, these strategies are inconvenient, costly, time-consuming, and troublesome in many fusion …

Conclusions & future insights

The subject of medical image fusion briefly discussed in this recent survey. To begin with, the study describes the various medical imaging modalities used in the MMIF in detail. Before moving on to more advanced MMIF approaches, we described several MMIF databases and the main processes with fusion rules workflow. Research on MMIF algorithms is summarized in this publication. Comparative image fusion studies involving frequency fusion, spatial fusion, decision fusion, deep learning, hybrid …

Declaration of competing interest

The authors of this manuscript declare no conflict of interest. …

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