BIOMEDICAL IMAGE PROCESSING: ANALYZING AND FUTURE ASPECTS

Abstract

Applied mathematics, computer sciences, engineering, statistics, physics, biology, and medicine are just a few of the fields that have contributed to the interdisciplinary nature of the research field known as biomedical image processing, which has grown significantly in recent years. The field has grown significantly in importance with the incorporation of computer-aided diagnostic processing into clinical practices. As technology develops and more imaging modalities are used, new difficulties in effectively processing and analyzing massive amounts of data to produce high-quality data for illness diagnosis and treatment arise. The objective of this review is to acquaint students with the basic ideas and methods of medical image processing while igniting their interest in additional learning and research in the area.

Keywords: Biomedical, Image Processing,Nano-Tomograph,Picture Archiving and Communication Systems (PACS),Clinical diagnosis

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I. INTRODUCTION

The interdisciplinary field of biomedical image processing, which has expanded rapidly, draws expertise from a variety of disciplines, including applied mathematics, computer sciences, engineering, statistics, physics, biology, and medicine. Notably, computer-aided diagnostic processing has been included into clinical practices on a regular basis. The acceptance of many imaging modalities and the quick advancement of high technology, however, have led to new issues as a result of this increase. These difficulties include effectively processing and evaluating a sizable number of medical images to produce high-quality information essential for identifying diseases and prescribing appropriate treatments.

In recent times, the field of biomedical signal processing and image processing has seen substantial progress, often highlighted in various review articles [1, 2, 3]. Such reviews typically concentrate on classifying the techniques used to analyse pixel and voxel data, such as image segmentation, and their applications in diagnosis, treatment planning, and follow-up research. However, this paper deviates from the conventional approach and instead emphasizes the challenges associated with processing large volumes of medical images [4, 5, 6].

The volume of medical picture data has increased dramatically over the past few years, going from kilobytes to terabytes. The main cause of this increase is the development of medical image collection devices with higher pixel resolution and quicker reconstruction processing. For example, the Sky Scan 2011 x-ray nano-tomograph has a stunning resolution of 200 nm per pixel, and the high-resolution micro computed tomography (CT) provides images with staggering 8,000 8,000 pixels per slice, offering a remarkable 0.7 m isotropic detail detectability.

The advancement in medical imaging technology has led to a considerable increase in data size per image slice, with modern systems producing around 64 Megabytes (MB) of data per slice. The image resolution and reconstruction time of CT and MRI systems can now be further adjusted, enabling whole-body scans with resolutions that produce several Gigabytes (GB) of data per scan[7, 8, 9].

There are two distinct situations where huge medical image data is prevalent. First, picture archiving and communication systems (PACS) frequently produce a large amount of image data from thousands of individual photographs. Second, a sizable portion of picture data comes from a single comprehensive dataset that contains in-depth details of a particular medical examination or study [10].

The quick development of new medications and medical science has considerably helped both humanity and civilization. The surgical profession has been transformed by modern science. But a precise and correct disease diagnosis continues to be a necessary requirement for efficient treatment. Better diagnostic capacities are attained when bio-instruments become more complex.Clinical diagnosis, treatment, research, and education all greatly benefit from the use of medical imagery. While X-ray computed tomography and magnetic resonance imaging are two methods used in medical imaging that are frequently used to represent anatomical structures, they can also be an important tool for evaluating physiological functioning. The advancement of computer and imaging technologies has had a

profound effect on medicine, with the accuracy of medical diagnoses being directly impacted by the caliber of medical imaging. Consequently, the processing of medical pictures has received a lot of attention, especially in clinical applications that need to save and retrieve comprehensive images for later use.

II. INSIGHTS INTO BIOMEDICAL IMAGE PROCESSING

1. **Background:** Image processing involves collecting measurements in two-dimensional (2-D) or three-dimensional (3-D) space. These values, referred to as "image intensities," can be used in medical images to depict a number of physical processes, including X-ray radiation absorption, ultrasound acoustic pressure, and radio frequency (RF) signal amplitude. A scalar image is one in which only one measurement is made at each position in the image.

   Faster, more precise, and less invasive equipment have significantly revolutionized medical imaging over the past ten years. This advancement has prompted the construction of appropriate software, which has fueled the development of ground-breaking signal and image processing techniques. Among these algorithms, partial differential equations and curvature-driven flows are prominent topics in this survey paper.

   Data extraction from images continues to be a crucial method for scientific advancement in experimental, clinical, biomedical, and behavioral research. Mathematical models are the cornerstone of biomedical computing. In comparison to the visible light pictures and microscope images of the early 20th century, medical images nowadays are acquired utilizing a variety of techniques at all biological scales. Modern medical images are essentially geometrically organized collections of data samples that quantify a variety of physical events, such as the temporal variation of hemoglobin deoxygenating during brain metabolism or the transport of water molecules through and inside tissue.

   As a result of the expanding application of imaging, complex mathematical models of physiological function and dysfunction have been created by applying novel processing techniques and integrating data from numerous channels. Developing general-purpose software approaches based on rigorous mathematical foundations and establishing biomedical engineering concepts is a crucial research field. These techniques can be smoothly incorporated into whole therapy delivery systems, enabling more efficient image-guided procedures, such as biopsy, minimally invasive surgery, and radiation therapy.

2. **Types:** Analog image processing and digital image processing are the two main techniques used in image processing. For physical reproductions like printouts and images, analog or visual image processing methods are used. When using these visual tools, image analysts base their interpretation on a number of fundamental concepts. Beyond the area of interest, image processing depends on the analyst's knowledge and skills. In image processing using visual techniques, association is a crucial tool that enables analysts to combine their own knowledge with extra information to improve the image processing process.

Digital processing techniques facilitate the manipulation of digital images using computers. Since raw data obtained from imaging sensors on satellite platforms may contain deficiencies, it goes through various phases of processing to overcome these flaws and preserve the originality of information. The three fundamental phases that all types of data undergo when employing digital techniques are Pre-processing, enhancement, and display, and information extraction.
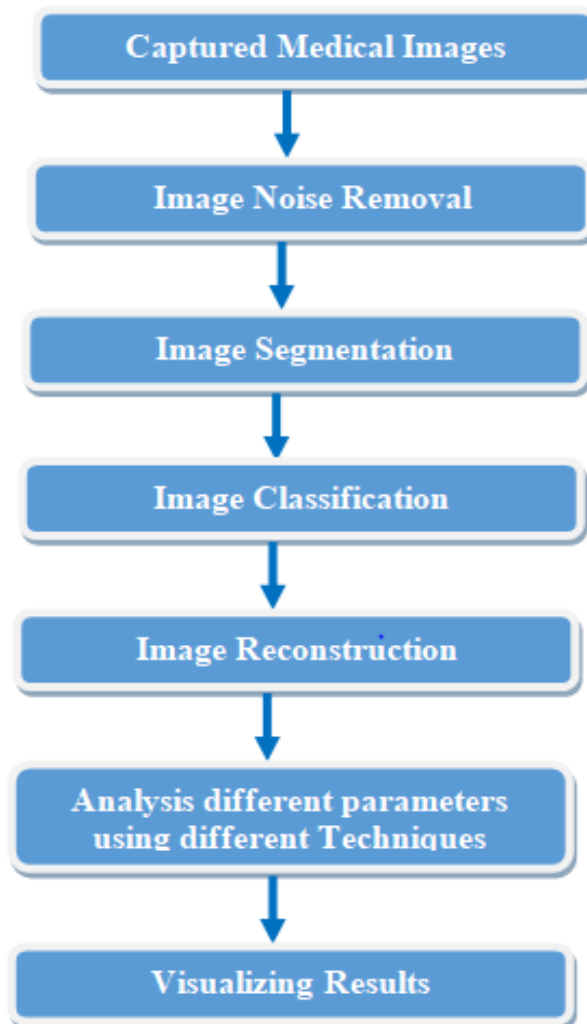
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Figure 1: Basic Image Processing Phase in Digital

The following are the basic phases in image processing:

- **Image Acquisition:** The process of capturing or obtaining an image using various imaging devices such as cameras, scanners, or sensors.
- **Image Pre-processing:** This step involves enhancing the image quality and correcting any imperfections or noise present in the acquired image. It includes operations like noise reduction, contrast enhancement, and image denoising.
- **Image Segmentation:** For the purpose of facilitating additional analysis, image segmentation separates the image into useful sections or objects. Based on similarities

in color, texture, intensity, or other visual characteristics, it entails dividing the image into separate zones.

- **Feature Extraction:** In this step, the segmented regions are mined for pertinent features or traits that can be used to represent and describe the image's items of interest..

- **Image Enhancement:** Techniques for image enhancement are used to increase the visual quality of the image for better processing or human perception. It uses techniques like sharpening, histogram equalization, and brightness correction..

- **Image Restoration:** Image restoration aims to recover the original image from a degraded or noisy version. It involves applying techniques to remove artifacts or blur introduced during the image acquisition process.

- **Image Compression:** Image compression reduces the size of the image while preserving essential information. It is crucial for efficient storage and transmission of images.

- **Image Transformation:** Image transformation involves modifying the image's spatial domain to achieve specific objectives, such as rotating, scaling, or warping the image.

- **Image Registration:** Image registration aligns multiple images of the same scene or object to ensure accurate comparison and analysis.

- **Object Detection and Recognition:** This step involves identifying and recognizing specific objects or patterns within the image using machine learning or pattern recognition techniques.

- **Image Analysis:** Image analysis is the process of drawing out important data or insights from image data that has been processed for use in a variety of applications, including automation, surveillance, and medical diagnosis..

- **Image Interpretation:** Image interpretation is the final step, where the processed and analyzed image data is interpreted to make informed decisions or draw conclusions based on the extracted information.

Low-level processing, as opposed to image analysis, which is frequently referred to as high-level image processing, includes both human and automatic methods that can be used without having prior knowledge of the particular image content. Regardless of the content of the image, these algorithms produce comparable results. For example, histogram stretching can improve contrast in both a radiograph and any vacation photo. As a result, low-level processing techniques are frequently used in picture enhancing software.

III. IMAGE PROCESSING ALGORITHMS AT VARIOUS STAGES

A common algorithm in medical imaging, image registration is especially well-liked for GPU implementations. Images and volumes can be transformed effectively thanks to the GPU's hardware capabilities for linear interpolation. Early GPU users for picture registration, such Hastreiter and Ertl (1998), were aware of its benefit for quick 3D interpolation. In a typical method, the CPU simultaneously runs a serial optimization algorithm to find the parameters (for example, translations and rotations) that achieve the best alignment between the two images, while the GPU calculates a similarity measure, frequently mutual information, over the images in parallel (Viola and Wells, 1997; Pluim et al., 2003; Mellor and Brady, 2005).

1. **Edge Detection Technique:** Edge detection is a fundamental image processing technique used to identify the boundaries or edges of objects and regions within an image. It plays a crucial role in various computer vision and image analysis tasks. The primary objective of edge detection is to locate significant changes in intensity or color values, which often correspond to abrupt transitions in the image.

There are several edge detection techniques, with some of the popular ones including:

- **Sobel Operator:** The Sobel operator determines an image's gradient magnitude, indicating areas with sudden changes in intensity. In order to calculate the horizontal and vertical gradients, convolution is used using two different masks.
- **Canny Edge Detector:** A multi-stage technique that offers reliable edge identification, the Canny edge detector. In order to identify edges, hysteresis thresholding is used in conjunction with non-maximum suppression to thin edges and Gaussian smoothing to reduce noise.
- **Laplacian of Gaussian (LoG):** The LoG operator uses zero-crossings in the image's second derivative to detect edges by combining Gaussian smoothing and Laplacian filtering.
- **Prewitt Operator:** he Prewitt operator computes gradients in the horizontal and vertical dimensions to identify edges, much like the Sobel operator.
- **Robert Operator:** Based on the variations in diagonal pixel brightness, the Robert operator employs two straightforward masks to identify edges..
- **Marr-Hildreth Edge Detector:** To find edges in a picture, the Marr-Hildreth edge detector employs the LoG operator with zero-crossings..
- **Zero-Crossing Detector:** By utilizing methods like the Laplacian or LoG, this method locates zero-crossings in the second derivative of the image.
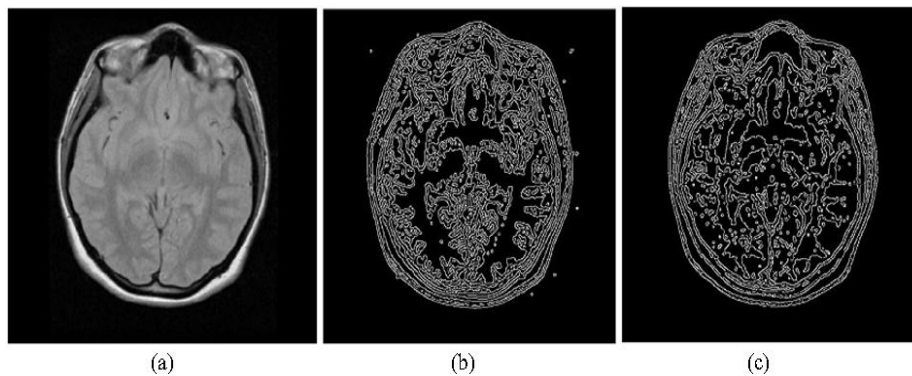

(a)   (b)   (c)

Figure 2: Edge Detection Using Canny Edge Detector

The application's specific needs and the properties of the image being processed will determine which edge detection method is used. Regarding edge detection accuracy, computing complexity, and noise sensitivity, each technique has advantages and disadvantages. Consequently, it is crucial to select an effective edge detection technique based on the current image processing requirement.

2. **Feature Extraction:** In image processing and computer vision, the process of extracting relevant and distinctive information from a picture in order to express its properties in a

more condensed and comprehensible manner is known as feature extraction. In order to complete tasks such as analysis, classification, or recognition, it is necessary to extract specific patterns, structures, or properties. Feature extraction contributes to processing simplification, increased computational efficiency, and increased algorithm correctness by lowering the dimension of the input.

Depending on the application and the kind of features needed, different feature extraction approaches are utilized. Typical techniques include:

- **Histograms:** Histograms can be used to record information about the overall appearance or texture of an image by representing the distribution of pixel intensities in the image.
- **Edges and Contours:** In order to define the boundaries of objects or regions in the image, edge detection techniques are used to detect sharp changes in intensity.
- **Corners and Key Points:** Corner detection techniques locate critical areas in an image when the gradient or curvature significantly changes. For matching and registration, these factors act as distinguishing characteristics.
- **Texture Descriptors:** To capture texture information in an image, methods including Local Binary Patterns (LBP), Haralick features, and Gabor filters are used.
- **Scale-Invariant Feature Transform (SIFT):**SIFT is an effective method for identifying critical locations and computing descriptors that are resistant to variations in illumination, rotation, and scale.
- **Histogram of Oriented Gradients (HOG):**Using local gradients to extract features, HOG is well suited for object detection and pedestrian recognition.
- **Principal Component Analysis (PCA):**The dimensionality reduction method principle component analysis (PCA) breaks down the original data into a new set of orthogonal features called principle components, which capture the most significant variations in the data.
- **Convolutional Neural Networks (CNNs):**Deep learning models called CNNs are very good at extracting features for many computer vision applications because they automatically learn hierarchical characteristics from the data.

The specific application, the type of data, and the desired information representation all influence the feature extraction approach selection. In many image processing and computer vision tasks, such as object recognition, image classification, image segmentation, and image matching, feature extraction is a critical step. It is essential for improving the effectiveness and precision of subsequent picture analysis and comprehension algorithms.

3. **Super-Pixel Classification using Slic Algorithm:** In computer vision and image processing, the SLIC (Simple Linear Iterative Clustering) algorithm is frequently used to classify superpixels. Superpixels are contiguous, compact zones that gather together comparable pixels to simplify the image while maintaining structurally significant details.

To efficiently produce superpixels, the SLIC algorithm combines the advantages of k-means clustering and picture segmentation. The following are the steps involved in superpixel classification using the SLIC algorithm:

- **Superpixel Generation:** Based on the desired number of superpixels, the image is initially divided into a grid of clusters (superpixels) of equal sizes. These clusters' cores are initially spaced regularly.
- **Feature Space:** The feature space for each cluster is defined locally, around the center of each cluster, which acts as a seed. The feature space often contains both spatial (x, y coordinates) and color information (e.g., RGB or Lab color space).
- **Assignment:** For each pixel in the image, the algorithm assigns it to the closest cluster center in the feature space. This process is guided by both color similarity and spatial proximity.
- **Update:** After assigning all pixels to the nearest cluster centers, the centers are updated to the mean of the pixels assigned to them. This step is repeated iteratively to refine the superpixel boundaries.
- **Regularization:** Superpixel boundaries may not be smooth during the iterative process, resulting in erratic forms. This can be fixed by using a post-processing step to regularize the superpixel forms, such as enforcing connection or enforcing compactness..

    The superpixels produced by the SLIC algorithm can be applied to a variety of image analysis tasks, including picture segmentation, object detection, and classification. Features from the superpixels, such as color histograms, texture descriptors, or deep learning representations, can be extracted for superpixel classification. Then, to categorize the superpixels into various groups or classes, machine learning methods such as support vector machines (SVM) or convolutional neural networks (CNNs) can be used.

    When image processing applications call for improved efficiency, more meaningful representation of picture regions, and lower computing complexity, superpixel classification utilizing the SLIC algorithm is very helpful. In computer vision applications, it provides more effective and context-sensitive image processing and understanding.

4. **Circular Hough-Transformation:** One effective method for finding circles or other circular shapes in an image is the Circular Hough Transformation (CHT). It is a modification of the common Hough Transform, which is commonly employed to recognize lines in images.

Following is how the Circular Hough Transformation operates:

- **Edge Detection:** Edge detection is the initial phase, and it entails employing edge detection techniques like the canny edge detector or any other appropriate edge detection algorithm to find edges in the image.
- **Parameter Space:** The Circular Hough Transformation generates a parameter space to represent potential circle centers for each edge point identified in the picture. A 2D accumulator array serves as the parameter space, and each cell in the array represents a potential circle's center.
- **Voting:** The Circular Hough Transformation casts a vote for every circle that could possibly pass through a given edge point in the parameter space. The matching cells in the accumulator array are updated with the votes.

- **Thresholding and Local Maxima:** After the voting process, the parameter space is analyzed to find local maxima. These local maxima correspond to potential circle centers, and their corresponding radius values determine the circle's size.
- **Circle Detection:** Finally, circles are detected by selecting the centers and radii associated with the local maxima in the parameter space. These centers and radii represent the detected circular shapes within the image.

IV. CONCLUSION AND DISCUSSION

Biomedical image processing continues to pave the way for groundbreaking innovations in medical science, offering valuable insights and enhancing clinical practices. The integration of computer-aided diagnostic processing has revolutionized clinical routines, streamlining the diagnostic process and contributing to improved patient outcomes. As technology continues to evolve, addressing the challenges related to processing and analyzing vast volumes of medical images remains a top priority for the medical imaging community. With continued research and development, medical image processing will continue to drive advancements in the medical field and shape the future of healthcare.

We have given an outline of several fundamental ideas in medical image processing in this paper. It is crucial to emphasize that none of these issues have been fully solved and that the algorithms we discussed still have a lot of potential for development. Particularly, segmentation is still a difficult operation that frequently requires interactive human involvement to produce the best results.

Despite these difficulties, significant strides in autonomous medical picture analysis have been made lately thanks to breakthroughs in hardware, acquisition strategies, signal processing methodologies, and mathematical frameworks. Particularly for diverse image processing tasks, curvature driven flows have demonstrated to be highly effective, having a substantial impact on the technological underpinning.

Medical imaging poses substantial mathematical challenges, cutting across various branches of mathematics. As we continue to progress in this field, every bit of help and innovation is valuable to push the boundaries and improve the state-of-the-art.
In conclusion, while there is still much to be accomplished, advancements in medical image processing have been made possible through interdisciplinary efforts, and ongoing research promises further enhancements in the future.

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