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EVALUATION OF EDGE DETECTION AND FUSION METHODS FOR ANGIOGRAPHIC IMAGE PROCESSING

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ABSTRACT

This study explores the application of digital image processing techniques to improve the diagnostic accuracy of coronary artery disease through enhanced analysis of angiographic images. A curated dataset of 40 grayscale, single-vessel angiograms was used to evaluate the effectiveness of various preprocessing and edge detection methods. Preprocessing steps included noise reduction, histogram equalization, and morphological operations aimed at improving image clarity and highlighting vascular structures. Three edge detection algorithms, Otsu, Canny, and Roberts, were applied, and their outputs were further combined using the Dempster-Shafer fusion theory. Performance was assessed using edge-based structural similarity (ESSIM) and the percentage error in vessel diameter measurements. The Canny algorithm demonstrated the highest individual accuracy, while the fusion of Canny and Roberts yielded superior results, achieving the lowest error and the highest similarity index.

KEYWORDS: medical image analysis, coronary artery disease, edge detection, image fusion, structural similarity

1. Introduction

The human ability to interpret the surrounding environment relies largely on visual information, but natural perception is often limited in identifying subtle details in images. Medical imaging, addresses these limitations through a set of methods dedicated to the acquisition, processing and analysis of digital images obtained using various specialized devices [1]. The process begins with image generation using medical equipment, followed by preprocessing steps that include noise removal, contrast correction, and contour enhancement; segmentation also enables the automatic delineation of anatomical structures of interest based on homogeneity criteria. The choice of this research direction is justified by its transdisciplinary nature, combining principles from physics, mathematics, and computer science to support medical analysis [1-3].

This paper explores the role of digital image processing in supporting the assessment of cardiovascular conditions, focusing on coronary pathology, a major cause of mortality associated with heart disease. The methodology involves applying a set of algorithms in successive stages to medical images, with the aim of examining how these techniques can detect vascular structures relevant to diagnosis [4]. Additionally, the integration of results is tested using a fusion algorithm, to determine whether combining different methods can lead to a more accurate vascular map. The impact of the results is analysed in comparison with the original images, using indicators such as structural difference measurement and percentage error calculation, to assess accuracy [5-11].

2. Materials and methods

2.1. Database

The dataset used in this study consists of 40 angiographic images from patients diagnosed with single-vessel coronary artery disease, examined using Coroscop (Siemens) and Innova (GE Healthcare) equipment at the Research Institute for Complex Cardiovascular Problems (Kemerovo, Russia). Out of the total set of images (ranging in size from 512×512 to 1000×1000 pixels), 40 relevant ones were manually selected, each containing contrast-enhanced passages through stenotic vessels.

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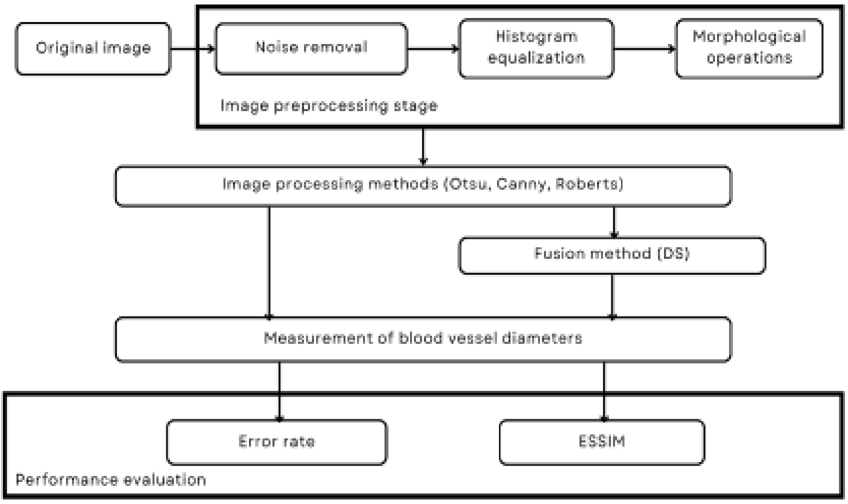

Fig. 1. *Flow chart of the proposed method*

2.2. Image preprocessing

The preprocessing stage plays a central role in image analysis, aiming to improve visual quality by reducing noise and eliminating irrelevant information. It also contributes to increased processing efficiency by reducing execution time and enhancing important details, such as edges. Noise filtering is essential because digital images can be affected by various types of noise introduced during acquisition, causing pixel intensity variations that do not reflect reality [12, 13]. Histogram equalization is frequently used to improve contrast by redistributing grey tones to highlight subtle details; an extension of this, CLAHE, allows for the enhancement of local contrast in poorly defined areas. Contrast adjustment involves transforming pixel values into an optimal range, increasing the visibility of relevant features [9]. Morphological operations, such as dilation, erosion, or contour and skeleton extraction, modify the structure of objects in the image and are applied using a structuring element [13].

2.3. Image processing algorithms

The Otsu method is an automatic technique used for determining the optimal threshold for binarizing grayscale images, based on the distribution of values in the histogram. The algorithm assumes the existence of two classes of pixels and determines the threshold that separates these classes by minimizing intra-class variance, ensuring a clear distinction between different regions of interest. Furthermore, the method iteratively evaluates all possible threshold values and selects the one for which the difference between the classes is maximized, meaning that pixels with values below the threshold are considered background, while those with values equal to or above represent the image foreground [14, 15].

The Canny edge detection method is considered one of the most effective techniques for detecting edges in images. The method aims to achieve accurate detection by minimizing errors, ensuring correct localization of edge points, and generating a single response for each real edge. It unfolds in five steps: applying a Gaussian filter to reduce noise, calculating the intensity gradient, eliminating false responses through non-maximum suppression, using a double threshold to identify potential edges, and retaining only the strong edges [16].

The Roberts edge detection method offers a fast and efficient approach for estimating the two-dimensional spatial gradient of an image, in order to highlight regions with abrupt intensity changes. The Roberts operator is typically applied to grayscale images and produces an output image in which each pixel reflects the magnitude of the local spatial gradient, which enables clear outlining of the vessel edges [17].

2.4. Dempster-Shafer Fusion for Edge Detection

The Dempster-Shafer theory is a mathematical method for evidence analysis, used to combine information from independent sources in order to estimate the probability of an event. It is based on belief functions and plausible reasoning, allowing uncertainty to be managed by gradually narrowing down a set of competing hypotheses as new evidence becomes available [18].

In image processing, the Dempster-Shafer method has been used to combine the results obtained through the Otsu, Canny, and Roberts methods in

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pairs of two methods, with each filter treated as a source of evidence. Their results are interpreted as fusion events, representing the classification of pixels into either "edge" (E) or "non-edge" (N) classes. The combination rule integrates the belief functions of each method, weighting their respective contributions through a coefficient w to obtain an optimal confidence level for edge detection [18, 19].

2.5. Image Processing Evaluation

The performance of the image processing methods was evaluated by calculating the percentage error and analysing structural similarity based on edge detection. The percentage error of the blood vessel diameters was calculated using the formula: $e = \frac{|M_R - M_i|}{M_R} \times 100\%$, where M_R represents the ground truth diameter values from the original images, and M_i corresponds to the diameter value measured after applying classical methods and the fusion algorithm [18].

ESSIM enables the evaluation of the degree of structural similarity between the original and processed images, in order to determine the accuracy of edge detection. However, ESSIM requires careful parameter tuning, as its performance can vary depending on the structure and complexity of the analysed images [20-22].

3. Results and discussion

To assess the impact of image processing on the diagnosis of coronary conditions, a workflow was implemented, consisting of preprocessing, edge detection and evaluation. The preprocessing stage included noise reduction, histogram equalization, and morphological operations, aiming to enhance clarity and highlight regions of interest. Three processing algorithms were applied to a set of 40 angiographic images to identify the optimal method for highlighting vascular structures, and the results generated were combined using a fusion method. The accuracy of each technique was analysed through measurements of vessel diameter. The quality of the results was quantified using the ESSIM algorithm, which estimates structural similarity between fused and processed images and the original image.

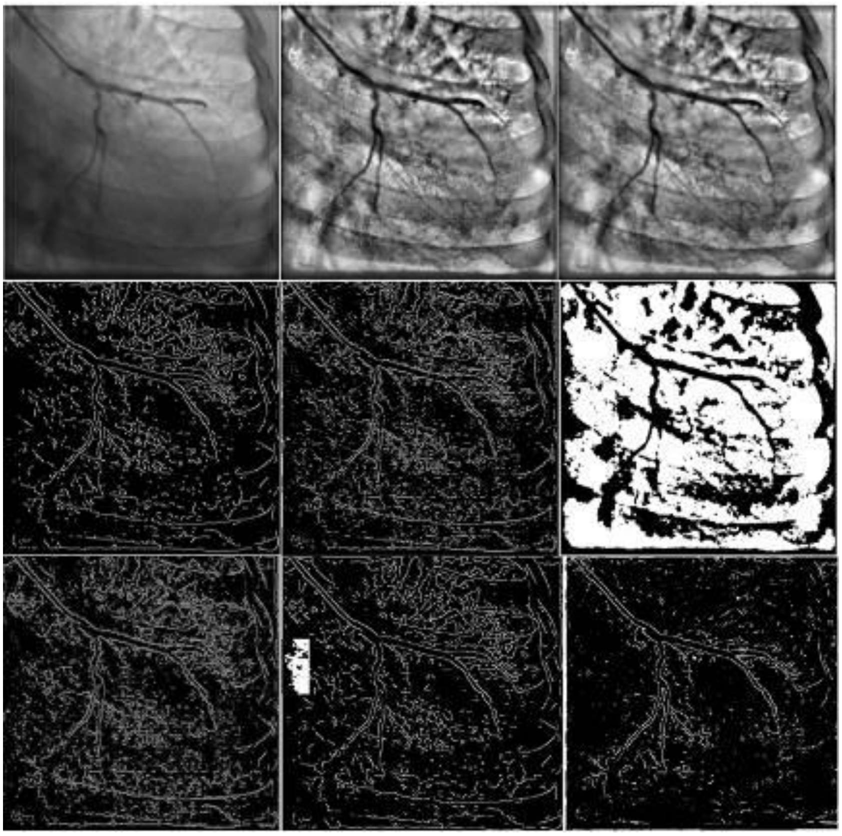

Fig. 2. *Examples of vascular map. (a) Original input image; (b) CLAHE; (c) Morphological operation; (d) Canny filter; (e) Roberts filter; (f) Otsu filter; (g) Canny-Roberts fusion; (h) Roberts-Otsu fusion; (i) Canny-Otsu fusion*

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Table 1. *Average blood vessel diameter values and mean percentage error*

	Ground truth	Otsu Method	Canny Method	Roberts Method
Average values	18.721	17.099	18.129	17.699
% error	-	*8.560*	*3.121*	*5.392*

	Ground truth	Otsu-Roberts Fusion	Otsu-Canny Fusion	Canny-Roberts Fusion
Average values	18.721	17.337	17.943	18.383
% error	-	*7.361*	*4.149*	*1.851*

Table 2. *Structural similarity index (ESSIM) calculated between the processed images and the original image*

	ESSIM values
Otsu Method	0.973335
Canny Method	0.967023
Roberts Method	0.974530
Otsu-Roberts Fusion	0.98801
Otsu-Canny Fusion	0.983434
Canny-Roberts Fusion	0.994312

The analysis of image preprocessing methods highlights the efficiency and limitations of each algorithm used. The noise reduction filter, although it does not produce visually noticeable changes, significantly contributes to improving the results of subsequent processing by eliminating noise. Although its values deviate from those of the original image, the main purpose of this filter is to clean the raw data. In contrast, histogram equalization proved to be the most effective preprocessing method, offering strong contrast and clearly highlighting the region of interest. The morphological operation further enhanced vascular structures and contributed to the improvement of visual quality, although with a smaller quantitative impact compared to histogram equalization.

In the processing stage, three methods were applied: Otsu, Canny, and Roberts. The Otsu method showed limitations, either causing loss of relevant information or false identification of areas of interest, while the Canny edge detection algorithm delivered the best results, both visually and in measured values, preserving essential edges without significantly affecting the region of interest. The Roberts algorithm resulted in less clear segmentation, with weak separation between useful and redundant information.

Evaluating the results of the fusion method indicates a clear advantage in terms of accuracy, as it generates lower error rates than any of the individual classical edge detection techniques. Examination of Figure 2 further highlights certain limitations of traditional filters like Otsu, Canny and Roberts, which frequently introduce artifacts such as duplicated or incomplete edges. In contrast, the fusion-based approach demonstrates enhanced reliability, producing more accurate vascular maps and minimizing segmentation errors, with percentage error as low as 1.85% in the case of Canny-Roberts fusion, while the smallest error among the classical algorithms is 3.12% when using the Canny algorithm.

Performance evaluation using the structural similarity coefficient (ESSIM) confirmed the superiority of the Canny method (among the three classical methods), although all three methods fell within the similarity range of 0.95–0.97 when compared to the original image. Finally, the application of the Dempster-Shafer fusion method demonstrated that integrating information from the Otsu-Canny and Otsu-Roberts pairs yields satisfactory results, better than each method on its own, while the Canny-Roberts fusion outperformed both the individual performance of the Canny method and the other two paired fusions, according to the values in Table 2.

4. Conclusions

The main objective of this paper was to identify the most effective image processing techniques for optimizing the diagnosis of coronary artery disease. Based on experimental values, the Canny method stood out for its superior performance in image segmentation, delivering the best results among the three analysed algorithms. The Roberts algorithm achieved comparable results, according to the evaluation using the structural similarity coefficient (ESSIM), while the Otsu method, although less effective in terms of quality, still recorded an acceptable level of fidelity. The application of these methods revealed a significant improvement in image quality, directly contributing to the facilitation of the medical diagnosis process.

Moreover, the use of the fusion algorithm based on Dempster-Shafer theory demonstrated greater robustness against variations in illumination and noise, and the low mean error in vascular diameter measurements supports the potential of this method as a viable alternative to conventional techniques. The most promising results were obtained from the fusion of the Canny and Roberts methods.

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