**‘ Advanced Noise Reduction Techniques for Bone Fracture X-ray Imaging’**

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**ABSTRACT**

Medical imaging, particularly X-ray examination, requires effective noise reduction and segmentation methods to improve diagnostic accuracy. This research compares several denoising algorithms, such as Gaussian Blur, Median Filtering, Wavelet Denoising, and Anisotropic Diffusion. Of these, the Median Filter is most effective in eliminating salt-and-pepper noise while maintaining important structures such as bones and fractures. Conversely, Gaussian Blur blurs images but can hide fine details and hence is not ideal for medical imaging where high edge clarity is needed. Furthermore, sophisticated methods such as Wavelet Denoising and Anisotropic Diffusion continue to improve noise filtering with structural preservation.

Felzenszwalb's graph-based segmentation approach stands out in object extraction because of its preservation of fine details, high boundary accuracy, and robust performance with noise. In contrast to K-Means clustering's misclassification of noise as object boundaries, or Mean Shift's over-smoothing of textures, Felzenszwalb accurately segments X-ray images without eliminating subtle intensity variation, essential in the detection of fractures. Also, its speed allows it to be used for real-time AI-assisted medical diagnostics without a need for extensive training data sets, making it an efficient and effective method of medical image processing.

Keywords: X-ray imaging, noise reduction, Median Filter, Gaussian Blur, Wavelet Denoising, Anisotropic Diffusion, Felzenszwalb segmentation, K-Means clustering, Mean Shift, medical image processing.

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## Chapter 1: INTRODUCTION

Medical imaging is an important tool in contemporary healthcare, and it helps diagnose and treat diseases. Of various imaging modalities, X-rays are commonly used to detect fractures, abnormalities, and diseases of bones and soft tissues. Nevertheless, the quality of X-ray images is generally degraded by noise added during image acquisition, which can mask important details and lower diagnostic accuracy. Effective noise reduction methods are needed to improve image clarity without degrading fine structures like bone edges and fractures.

Several noise reduction algorithms have been investigated to enhance the quality of X-ray images. Linear filters such as Gaussian Blur smooth images by averaging pixel intensities, effectively eliminating high-frequency noise. Yet, they can also blur fine details, making them less desirable for medical imaging where edge clarity is important. Non-linear filters, including the Median Filter, provide a more effective solution to the removal of salt-and-pepper noise with retention of critical structural details. Furthermore, techniques such as Wavelet Denoising and Anisotropic Diffusion offer improvements by selectively diminishing noise while ensuring edge sharpness.

Aside from noise reduction, proper segmentation of objects in X-ray images is crucial for medical diagnosis. Old techniques such as K-Means clustering cluster pixels according to intensity values but commonly break down in noisy images, causing noise to be misclassified as object edges. Mean Shift performs well in retaining small details but over-smoothes the image, thus not very good in identifying subtle fractures. Graph-based segmentation algorithms, specifically Felzenszwalb's algorithm, are a stronger method through region grouping based on texture and intensity gradients to achieve improved boundary accuracy.

Felzenszwalb's segmentation algorithm is especially useful for medical image processing due to its ability to handle noise without sacrificing fine details. In contrast to clustering-based algorithms, which rigidly categorize pixels into pre-defined groups, Felzenszwalb's algorithm adjusts dynamically to local intensity changes, making it ideal for fracture and other small anomaly detection. Its efficiency in computation also makes it viable for real-time use in AI-aided diagnostics, where both speed and accuracy are paramount.

In this research, various noise removal and segmentation methods for X-ray images are investigated and compared based on their efficiency in maintaining key medical details. Through the comparison of Gaussian Blur, Median Filtering, Wavelet Denoising, and Anisotropic Diffusion for removing noise, and Felzenszwalb's segmentation for separating objects, we bring to light the most appropriate methods for the enhancement of the quality of X-ray images. This research, through its findings, contributes towards enhanced automatic medical image analysis, providing more accurate and effective diagnostic tools.

## Chapter 2 : PROBLEM STATEMENT & OBJECTIVES

1. **Problem Statement:**

X-ray imaging finds extensive application in medical diagnostics, yet with the presence of noise and poor segmentation, the accuracy of medical analysis is compromised. The conventional noise reduction methods tend to blur significant details or not effectively eliminate noise. Similarly, standard segmentation techniques such as K-Means clustering and Mean Shift tend to lose fine structures like fractures and fine bone details. It requires an optimal method that is capable of getting rid of noise effectively but leaves edge definition intact and correctly segments important medical structures.

1. **Objectives:**

* **Assess Noise Reduction Methods:** Compare the efficiency of Gaussian Blur, Median Filtering, Wavelet Denoising, and Anisotropic Diffusion in noise reduction without losing essential image features.
* **Compare Segmentation Techniques:** Evaluate the efficiency of graph-based segmentation (Felzenszwalb) with conventional clustering methods such as K-Means and Mean Shift for object extraction from X-ray images.
* **Find the Optimal Method for Medical Imaging:** Identify the best combination of noise reduction and segmentation methods to maximize the quality of X-ray images for better medical diagnosis.
* **Ensure Computational Efficiency:** Choose a method that achieves accuracy and computation speed balance in order to facilitate real-time AI-enabled medical imaging applications.
* **Enhance Automated Medical Image Analysis:** Help develop robust computer-aided diagnostic tools through the optimization of noise removal and object segmentation methods.

**Chapter 3: DATASET SELECTION & DETAILS**

The use of an effective dataset is important in order to analyze the performance of noise reduction and segmentation methods in medical imaging. For this research, X-ray image datasets containing labeled bone fracture cases are selected. They offer real-case medical images with different levels of noise, enabling a comprehensive comparison of various filtering and segmentation approaches.

1. **Dataset selection criteria:**

The datasets were chosen according to the following criteria:

**Medical Relevance:** The datasets have X-ray images with explicit fractures annotations and thus are appropriate for testing segmentation and noise reduction methods.

**Diversity:** The data sets contain X-ray scans of various anatomical areas (e.g., elbows, wrists) with different noise levels and contrast.

**Labeled Data:** The availability of labeled images (fractured and non-fractured) makes it possible to accurately assess the performance of the techniques implemented.

**Availability:** The data sets are openly available from GitHub and Kaggle, allowing for straightforward incorporation into analysis and research pipelines.

1. **Dataset details:**

**GitHub Bone Fracture Dataset**

**Source:** GitHub Repository[(https://github.com/Alkoby/Bone-Fracture-Detection/blob/master/Dataset/test/Elbow/patient11236/study1\_positive/image2.png)](CV_assignment)

**Data Type:** X-ray images with anatomical region as category, i.e., elbow and wrist.

**Labeling:** Positive (fractured) or negative (non-fractured) classification of each image.

**Resolution:** Varies but inherently adequate for medical image analysis.

**Application:**

* Used to test segmentation methods for the purpose of bone structures and fractures extraction.
* Aids in determining the effect of noise reduction filters on fine structures.

**Kaggle Bone Fracture Detection Dataset**

**Source:** Kaggle[(https://www.kaggle.com/datasets/vuppalaadithyasairam/bone-fracture-detection-using-xrays?utm\_source=chatgpt.com)](CV_assignment)

**Data Type:** Large dataset of X-ray images labeled for detecting bone fractures.

**Labeling:** Images are marked as fractured or non-fractured.

**Diversity:** Has scans from more than one patient, providing a diverse set of noise levels and contrast variations.

**Application:**

* Useful for applying noise reduction algorithms such as Gaussian Blur, Median Filtering, and Wavelet Denoising.
* Is a standard dataset for the purpose of checking segmentation accuracy to detect bone fractures.

1. **Justification of Dataset selection:**

 



**CHAPTER 4: NOICE REDUCTION**

X-ray medical images typically experience noise through causes like exposure to radiation, sensor constraints, and transmission-related artifacts. This noise may blur vital details to such an extent that fractures as well as bone structures become impossible to identify or identify accurately. In order to enhance the clarity of X-ray images without causing a loss to essential details, numerous noise elimination processes are deployed. In our research, a mix of linear and non-linear filtering methods, combined with novel denoising algorithms, are utilized to enrich the image readability.

The following noise suppression methods are utilized and compared:

* Gaussian Blur (Linear Filter)
* Median Filter (Non-Linear Filter)
* Wavelet Denoising (Frequency-Domain Approach)
* Anisotropic Diffusion (Edge-Preserving Smoothing)

Each approach is assessed on the basis of how well it can eliminate noise while preserving significant structural details.

**Noice Reduction Techniques applied:**

**Gaussian Blur (Linear Filter)**  
**Description:** Common linear filter that uses a Gaussian kernel to blur the image by averaging pixel values in a weighted fashion.  
**How It Works:**

* A Gaussian function is used for neighboring pixels.
* Greater weight to nearer pixels, diminishing high-frequency noise.

**Effectiveness:**

* Effective for eliminating overall noise.
* But it blurs the finer details, so it's not good for medical images.

**Application:**

Frequently employed as a preprocessing stage in image processing chains.

**Median Filter (Non-Linear Filter)**

**Description:** A non-linear filter that substitutes the value of each pixel with the median value of its neighborhood pixels.

**How It Works:**

* Instead of taking averages of pixels, the median is chosen.
* It eliminates noise while maintaining edges.

**Effectiveness:**

* Most effective at removing salt-and-pepper noise.
* Saves edges compared to Gaussian Blur.

**Application:**

Often applied in medical image processing as it preserves thin details such as fractures.

**Wavelet Denoising (Frequency-Domain Approach)**

**Description:** A wavelet transform-based method that filters noise from signal components of use.

**How It Works:**

The image is converted to various frequency components.

Noise at high frequencies is eliminated, while low-frequency structures (e.g., bones) are preserved.

**Effectiveness:**

* Eliminates noise without over-blurring fine structures.
* Better than Gaussian Blur for medical images.

**Application:**

Applied in state-of-the-art medical imaging devices to improve X-rays.

**Anisotropic Diffusion (Edge-Preserving Smoothing)**

**Description:** A mathematical technique that smoothes noise but maintains edges.

**How It Works:**

* Edges are detected by the algorithm and kept from being excessively blurred in these areas.
* Selective removal of noise in non-edge regions.

**Effectiveness:**

* Removes random noise efficiently.
* Blurs significant structures such as fractures not at all.

**Application:**

Applied in MRI and X-ray imaging where the preservation of edges is essential.

**Visual comparison of Noise Reduction:**

|  |  |
| --- | --- |
| **Stage** | **Image Output** |
| Original Image |  |
| Gaussian |  |
| Median |  |
| Wavelet |  |
| Anisotropic |  |
| K-Means segmentation |  |
| Mean shift segmentation |  |
| Graph based segmentation |  |
| Graph-Based Segmentation (Felzenszwalb) |  |
| Ground Truth Mask |  |
| Predicted Mask |  |
| Intersection(overlap) |  |
| Noisy |  |
| De-Noised |  |

**CHAPTER 5: RESULTS & DISCUSSIONS**

**Evaluation Metrics:**

To evaluate the efficiency of our segmentation approach for detecting bone fractures, we employed three most important performance metrics:

* **Intersection over Union (IoU) Score** – Indicates the overlap of predicted and ground truth segmentation.
* **Dice Coefficient** – Assesses similarity of the predicted and ground-truth segmented regions.
* **Pixel Accuracy** – Specifies the proportion of correctly classified pixels in the image.

**Result Analysis:**

|  |  |  |
| --- | --- | --- |
| **Metric** | **Score** | **Innovation** |
| IoU | 0.9332 | High overlap between actual and predicted segmentation, which demonstrates correct region identification. |
| Dice Coefficient | 0.9654 | High degree of similarity between ground truth and predicted masks, which demonstrates high-quality segmentation. |
| Pixel Accuracy | 0.9818 | Most pixels being correctly classified ensures accurate bone structure segmentation. |

**Discussion and Interpretation:**

**Intersection over Union (IoU) Score – 0.9332**

* A high IoU score of 93.32% confirms that the predicted segmentation closely resembles the true ground truth mask.
* This implies that our model identifies fractures and bone structures with great accuracy, minimizing false positives and false negatives.
* The minor drop from 1.0 reflects small boundary mismatches, but the outcome is extremely reliable for medical use.

**Dice Coefficient – 0.9654**

* Dice coefficient (96.54%) is a strong proof of overlap between the segmented regions and the regions predicted.
* Close to 1.0 is an indication that the segmentation model has a high ability to identify fine details and hence is capable of fracture detection.
* The high score guarantees the extracted bone structures have distinct clear boundaries, lessening false classification.

**Pixel Accuracy – 0.9818**

* The 98.18% Pixel Accuracy proves that most pixels in the X-ray images are accurately labeled.
* This figure confirms the model's strength in identifying bones from the background.
* In noisy or weak fracture cases, the model remains highly accurate, and hence is suitable for actual medical diagnosis.

**CHAPTER 6: INNOVATION OF THE STUDY**

An Approach to perceptual loss aimed to improve the quality of denoised X-ray images by incorporating high-level feature similarities rather than just relying on pixel-wise accuracy. Instead of traditional loss functions like Mean Squared Error (MSE) or Mean Absolute Error (MAE), an integrated feature-based comparison using a pretrained VGG16 network has been done , ensuring that the restored image preserved fine structural details crucial for medical image analysis.

**1. Transformed Grayscale Images into RGB**

As VGG16 is used for three-channel RGB images, but X-ray images are grayscale which is single-channel, we initially transformed the grayscale images into RGB mode. Transforming the grayscale images into RGB made the images compatible with the VGG16 model so that meaningful feature representations can be extracted from deeper layers of the network.

**2. Employed a Pretrained VGG16 Model to Extract Features**

We used a pre-trained VGG16 model, loading it without the fully connected layers. The model was pre-initialized with ImageNet weights, which would make sure that it could extract useful hierarchical features from images. Rather than utilizing the whole network, we took features from the 'block3\_conv3' layer, which extracts mid-level structural and texture information. Freezing the weights of VGG16 avoided training the feature extractor, ensuring that it was only used for comparison.

**3. Computed Feature Loss**

For the purposes of comparing structural details between the ground truth and denoised image, we took feature maps from the VGG16 model. By computing the Mean Squared Error (MSE) between the feature maps, we imposed similarity between the high-level structures of the predicted and original images. This forced the denoised image to hold fine-grained features and textures instead of being smoothed excessively.

**4. Combined Perceptual Loss with Pixel Loss**

We combined perceptual loss with pixel-wise MSE loss to improve the overall loss function. The perceptual loss made sure that the model retained high-level features, whereas the pixel loss ensured pixel-wise similarity between denoised and ground truth images. The combined approach weighed low-level precision against high-level feature consistency and provided visually clear and medically relevant denoised X-ray images.

**Advantages of This Approach:**

* **Maintains Structural Information**

In contrast to regular MSE loss that produces hazy outputs, perceptual loss maintains valuable structures like bone fractures, textures, and anatomical borders.

* **Improved Feature-Based Similarity**

Rather than processing images as mere grayscale intensity values, this approach allows the model to learn higher-level feature correspondences, which are essential for medical imaging applications.

* **Reduces Over-Smoothing in Denoising**

Conventional denoising techniques tend to blur edges and small textures, but perceptual loss avoids this by retaining sharper details and contrast, enhancing diagnostic consistency.

* **Enhances Generalization to Various Noise Types**

Because the model is trained from a pretrained feature extractor, it is able to generalize well across different X-ray noise patterns and artifacts and thus is more robust than purely pixel-based loss functions.

**Why This is Innovative?**

* Maintains High-Level Features – Retains shapes, edges, and textures intact in the denoised X-ray.
* Superior to MSE Alone – In contrast to plain pixel-based loss, this approach avoids blurring artifacts typical of deep learning-based denoising.
* Medical Image Suitability – Assists in preserving important bone structures in fracture identification.

**CHAPTER 7: CONCLUSION**

This project effectively implemented noise reduction and segmentation methods in enhancing the quality of X-ray images and precise identification of bone fractures. Using Gaussian Blur, Median Filtering, Wavelet Denoising, and Anisotropic Diffusion, we actually minimized noise while retaining essential structures in medical images. Out of these techniques, the Median Filter was found most useful in removing X-ray noise since it maintained fine details without over-blurring.

For segmentation, Graph-Based Segmentation (Felzenszwalb's Algorithm) was used because it has a better capability to maintain object boundaries, deal with noise, and identify subtle fractures compared to conventional clustering methods such as K-Means. The model had high segmentation accuracy with an IoU score of 0.9332, Dice Coefficient of 0.9654, and Pixel Accuracy of 0.9818, which shows accurate bone structure extraction and low misclassification.

**Key Takeaways:**

* **Noise Reduction:** Median filtering and wavelet denoising were best suited to maintain the detailed bone structure and eliminate noise.
* **Segmentation Performance:** Felzenszwalb's algorithm successfully identified fractures with good accuracy and boundary accuracy.
* **Evaluation Metrics:** The high IoU, Dice, and Pixel Accuracy values affirm the model's accuracy for medical purposes.