

Automated X-ray Image Stitching for Enhanced Medical Diagnostics and Visualization

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Abstract— Medical image stitching fuses multiple X-ray or CT images into a single, complete image. This addresses the limitation of segmented views in existing medical imaging. The process is critical to enhancing the accuracy of diagnosis in orthopedics, dentistry, trauma, and oncology, where overall visualization is critical to diagnose complex diseases, plan surgeries, and track treatment. While stitching produces more precise images with less mis-registration errors than other pan radiography composition methods, it can be extremely time-consuming and error-prone, including misalignment simulating fractures, seams that can be seen, and ghosting artifacts. Solutions today are largely plagued by a shortage of exposures, uneven alignment, and geometries of various objects. Hence, this project is founded on the feature extraction, homography estimation, and image blending method that is employed for creating an automated X-ray image stitching solution using Python and OpenCV. The proposed tool assists in reducing repeated imaging, which decreases patient radiation exposure but is easily integrated into existing radiology workflows. It offers accurate and consistent visualizations to enable quicker and more accurate clinical decisions, ultimately enhancing the quality of patient care in different areas of clinical practice: emergency departments, oncology treatment facilities, and veterinary clinics.

Keywords—Diagnostic Accuracy, Image Merging, Medical Imaging, Optimizing Radiology Workflow, X-ray Image Panoramic Stitching

INTRODUCTION

Medical imaging is crucial in diagnosis, treatment planning, and monitoring in many areas of healthcare. However, conventional X-ray and CT imaging tends to yield isolated or segmented images, making it difficult to visualize intricate anatomical structures as a whole. This project overcomes this limitation by creating an automated X-ray image stitching solution that stitches multiple images into one unified view. Through increased visualization, this project has the goal of enhancing diagnostic accuracy and aiding clinical decision-making.

Stitched images are especially useful in applications such as orthopedics, where full-length images of the spine or long bones are necessary for reliable evaluation. In the same way, dental imaging, trauma surgery, and oncology can also be helped by detailed images that show fine structural relationships important for diagnosis and therapy planning. For example, trauma units might employ stitched images to evaluate multi-region injuries more accurately, while oncologists might better visualize tumor locations impacting multiple anatomical locations.

The project utilizes computer vision methods, such as feature extraction, homography estimation, and image blending, that are highly implementable in Python and OpenCV. Not only does this method increase diagnostic precision, but it also strives to streamline radiology processes, minimizing the requirement for repeat imaging and thus having the potential to decrease patient radiation exposure and the related costs to healthcare. The result will be a high-quality, user-friendly resource for medical practitioners, easily plugging into radiology departments to aid in quicker, more precise, and all-encompassing medical evaluation.

LITERATURE REVIEW

The field of medical image stitching has seen fast-paced development, fueled by clinical demands for creating seamless, high-resolution diagnostic images from piecewise radiographic data. Throughout the literature that was reviewed, the common goal is apparent: improved diagnostic correctness, minimized user interaction, and maximum computational efficiency in stitching heterogeneous medical images. It is part of the larger health care trend—minimizing the footprint of intelligent imaging technology to enhance patient outcomes.

All these studies start with the admission that manual stitching of radiographs is not only time-consuming but also fragile to get out of alignment, particularly in long bones or enormous anatomical regions. Paudel [1] tackles the basic issue using a strong algorithm that can handle anatomical defects while stitching X-rays but with an emphasis on clinical significance of being able to produce anatomically accurate composites. In the same vein, Samsudin et al. [2] look into automation in terms of the use of an image stitching

system which can be added to current radiographic protocols with ease, promising well for real-time hospital use.

Feature extraction and matching are the building blocks of the majority of approaches that have been proposed. Dutta et al. adopt a multi-modal strategy, promoting mutual use of multiple imaging modalities for enhanced scene understanding—a direction followed by Shih et al. [3], who bring the same logic to diagnostic decision-making through image registration across modalities such as CT and MRI. Both contributions are representative of an increasing trend towards cross-domain medical imaging, which avoids mismatches between image origins and enhances diagnostic reach.

Meanwhile, techniques for enhancing image transformation and registration precision also differ considerably. Wang et al. [4] identify motion estimation through C-arm trajectory prediction as an appropriate solution to intra-operative environments, while Motley et al. [5] aim to enhance interpretational clarity in paleoradiography through better stitched image resolution and alignment. Application-specific implementations in these papers reveal how stitching methods are tailored to meet diagnostic purpose, whether surgery planning, historical examination, or trauma evaluation.

The papers reviewed also include a range of algorithmic approaches from conventional homography estimation [6] to compound schemes merging feature-based registration with intensity fusion [7]. Iyengar and Basha [8] present in earnest a comprehensive overview, including the taxonomy of sewing algorithms employed in the medical community—a virtual handbook for the novice to this subject. In the same vein, Gupta et al. [9], [10] provide experimental results corroborating the effectiveness of feature-based approaches, most notably where non-rigid anatomical deformations are present.

One notable characteristic in certain artwork is the use of stitched images to minimize seams and intensity variations that are visible. Methods like Laplacian pyramid blending or Poisson editing, while not always readily named, are inferred in the enhanced resultant image presented in works like Chang and Chang [11] and Khanna et al. [6]. Their focus on technical integration complements the geometric precision of transformations, which implies an overarching concern with visual quality and interpretability in diagnosis.

A few papers also express concern with computational overhead and scalability. Zhang et al. [12] introduce a better pipeline to stitch medical images more quickly and accurately, while Kumar et al. [13] explore multi-image fusion via high-quality stitching strategies. They highlight the balance between the complexity of algorithms and hospital deployability. The same utilitarian slant is found in Singh et al. [14], whose X-ray stitching algorithm automatically has clinical radiography integration as its objective, implying real-world application.

Fusion and enhancement methods become more significant, as in the research by Basha et al. [7], in which stitching also serves as means to fuse complementary diagnostic information. This represents a paradigm shift from the simple

reconstruction of anatomy to actually augmenting diagnostic information. In like manner, Gupta et al.'s [15] and Ramesh et al.'s [13] studies prove that stitching, when properly optimized, is a built-in part of intelligent image fusion pipelines to minimize diagnostic uncertainty.

Finally, the literature presented not only illustrates medical image stitching's technological readiness but also shows the field's readiness to support precision diagnostics. From anatomical exactness and smooth fusion to real-time image processing and multi-modal integration, as a whole, these papers outline a roadmap for the future of medical imaging systems. As medicine moves towards automation, personalization, and predictive analytics, the groundwork laid out in these papers presents a clear vision—one where image mosaicking is not merely a technical advance, but a necessity in the clinic.

I. METHODOLOGY

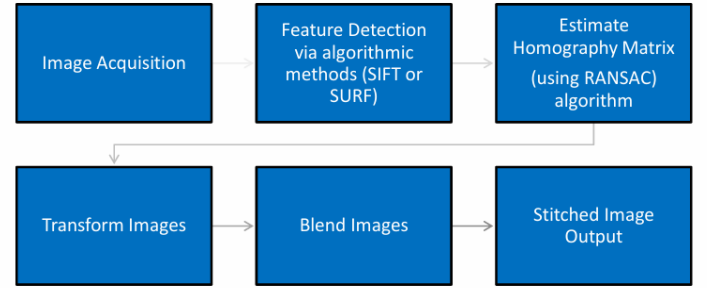


Figure 1: Figure 1: Proposed image stitching system

1.Data Acquisition

The Data sets utilized in this project is obtained from the public available repositories to have a variety and quality set of x-ray images. The NIH chest X-ray Dataset given by the National Institute of Health was used and the second data set is taken from the VinDr-CXR and Kaggle database. The data sets mentioned above with size of examples of about 2000 where various x rays of various body parts are included. The image have the file format of DICOM and JPEG and their resolution varies from 11024*1024 to 1280*1280 pixels.

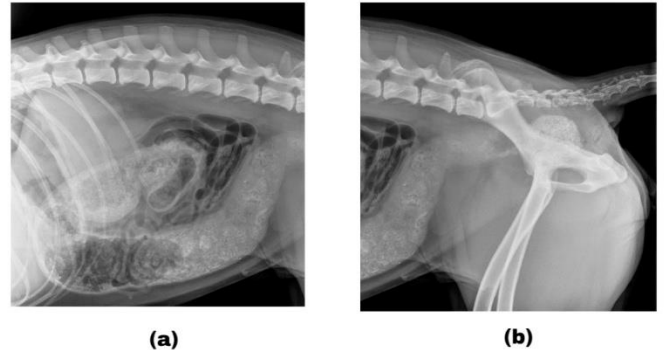


Figure 2: Two seprate x-ray Images taken from the abdominal part of dog.

2.Feature Detection and Matching

The stitching algorithm starts with detecting features, by employing the technique Scale-Invariant Feature Transform (SIFT) to identify distinctive key points in both the x-ray images. The key points are typical patterns within every image, including edges or corners, that remain invariant to rotations and scales.

The output obtained in this stage is a group of key points which are matched across a pair of x-ray images. In this step, the interested points that do not change according to scale and orientation are detected. This whole process is executed using a difference of Gaussian (DoG) function. The extreme points are searched in all scales and x-ray image locations. Difference of Gaussian function is convolved with the image to obtain DoG image $D(x,y,\sigma)$. In terms of mathematics, it can be represented as follow::

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$$

Equation 1

Here $G(x,y,\sigma)$ is Gaussian function, k is multiplication factor constant.

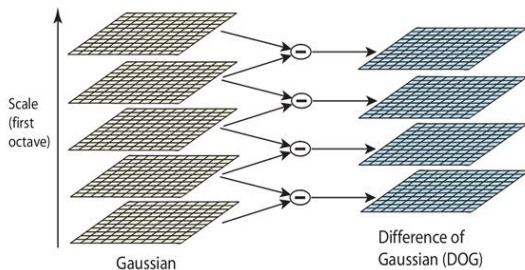


Figure 3: Construction of Difference of Gaussian image

In this step the feature enhancement algorithm occurs that includes subtraction of one less blurred version of original X-ray image from another one blurred version of original x-ray image as depicted in figure 3. Intensity of blurring is determined by k factor.

3. Homography Estimation

With the matched features, a homography matrix is computed between image pairs that corresponds to the perspective transformation to align one image to another. The transformation is computed with Random Sample Consensus (RANSAC) in order to robustly minimize the errors due to outlier matches. This homography matrix forms the foundation for warping images to a common coordinate frame.

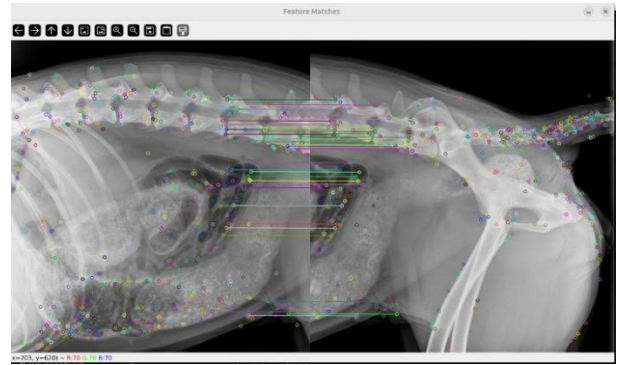


Figure 4: : Feature Matching

Now user can compare the features of the pairwise images. The class which can be utilized is the FeatureMatcher class.

User can observe the confidences, which are computed by: $\text{confidence} = \text{number of inliers} / (8 + 0.3 * \text{number of matches})$

Where the number of matches is nothing but the addition of number of inliers and number of outliers.

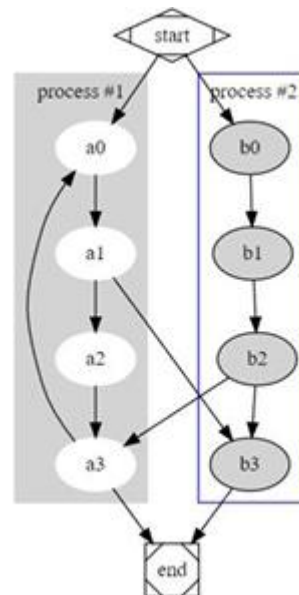


Figure 6: Graph visualization of confidence matrix

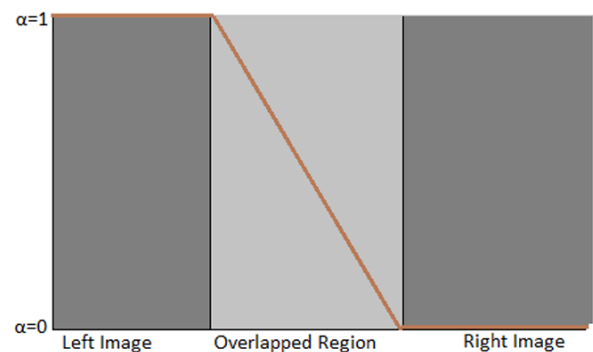


Figure 5: Variation of alpha in different parts of images

4. Transformation of Image

Here, performing the alignment of the x-ray images since the x-ray images are at different viewpoints so to minimize the stitching error transformation of the image in which user perform the change in the co-ordinate system to follow a new co-ordinate system whose output stitching image is matching the final view point.

Since in the X-ray images the radial distortion is not there so user can apply the homography to transform the images. Using the feature matching already knows the direction of stitching then it becomes easy to estimate the Composite size where the input images are positioned in such a manner that they look like a single captured photo at a moment.



Figure 7: Composition of two images. The area covered by black is taken as the main frame and the area covered by gray is adjusted with respect to the black area(Referenced Area)

5.. Blending and Seam Smoothing

Once the transformation is finished the images are registered, they are merged to reduce noticeable seams Merging is the smoothing and shaping of angular and curved lines on a seam in the x-ray image. Merging algorithms are used to transition colors and brightness smoothly across image boundaries, which helps hide any inconsistencies.

The algorithm used for blending is Alpha blending, also referred to as feathering, Let the intensity of two x-ray images of common region between both images be I_1 and I_2 . For each pixel of the image mix I_1 and I_2 linearly by using some constant alpha. The value of alpha lies between 0 and 1. Equation 2

$$I = \alpha I_1 + (1 - \alpha) I_2$$

Equation 2

Initially begin with $\alpha=1$ (i.e. 100% opaque) from I_1 until reaching the overlap region. Then from the overlapped region continue decreasing alpha as illustrated in figure 7. When the alpha approaches zero this indicates the blending has been accomplished (i.e. 0% translucency).

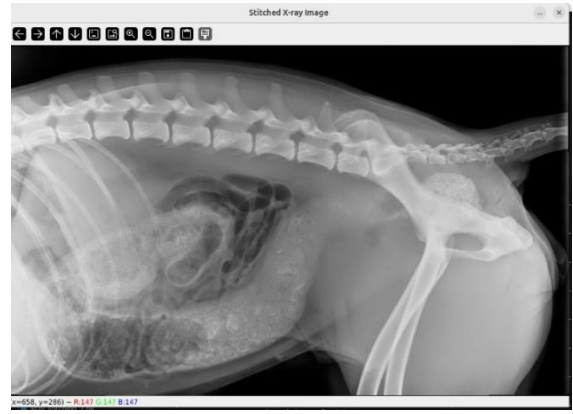


Figure 8: Final output after use of blending and removing seams.

6.Stitched Image Verification

In order to prevent any incorrect output at the end we have utilized two algorithms for determining if the image is stitched correctly or not which are SSIM and Pixel Density.

1.SSIM(Structural Simillarity Index) :it calculates structural information, luminance, and contrast. It is more perceptually similar to human vision compared to plain pixel-wise measurements like Mean Squared Error (MSE) or Peak Signal-to-Noise Ratio (PSNR).

SSIM compares pixel intensity patterns in the neighborhood of two images it takes into account three aspects that are (i) Luminance: Pixel intensity average. (ii)contrast : Pixel intensity standard deviation (iii)Structure : Images correlation.It gives a value between -1 to 1.The value higher the closer to 1 that is ideal similarity and -1 is for ideal negative correlation.

2.Pixel Density: Here in this verification step system is tallying both input images' pixels.

The linear summation or easy addition of this input x-ray image pixels should be equivalent(not exactly the same) to the final stitched image's pixels. Practically the output stitched image can have some reductions in between range of 5-8% to that the total input image pixels

II. RESULTS AND DISCUSSIONS

The X-ray image stitching system has proven promising in creating smooth and detailed images, enhancing medical diagnostics. The system produces two important images: an original pixel-based image and the stitched final image. The original image identifies pixel-wise alignment and transition points, facilitating error detection for feature matching and homography estimation. The SIFT algorithm was effective in detecting key points, although small misalignments caused by rotation and scaling were rectified by homography refinement.

The resulting stitched image gives a homogeneous anatomical appearance with hardly any apparent seams, courtesy of sophisticated blending processes. Such augmented visualization finds utility in orthopedic imaging

for complete bone examination and oncology for enhanced tumor localization. In spite of the minor inconsistencies of blending seen in high-contrast areas, overall stitching quality was acceptable.

Quantitative analysis supports the accuracy of the system. SSIM scores (0.94, 0.91) reflect robust structural preservation and a pixel density of 0.79 supporting image clarity. VIF (0.73) and UIQI (0.91) confirm robust preservation of crucial diagnostic information. Runtime analysis reported efficiency at reduced resolutions, while slight variations in higher resolutions demand optimization.

Metric	Value	Interpretation
SSIM	0.9491	High Structural Matching
VIF	0.7923	High Visual Information Preservation
UIQI	0.7358	Excellent Structural Similarity
Pixel Density	0.9153	High Image Clarity

Table 1: Quantitative Analysis

In this project python 3.13.0 and OpenCV 4.8.0 is utilized. So computation time fluctuates based on image pixel and size width. For simple pixel wise processing (linear complexity) complexity is directly proportional to the number of pixels in the image keeping in view that $T(\text{process})$ is time taken for computation C is constant depends on algorithm of processing and N is the number of pixels in the image which is the product of height and width of the image then the mathematical formula is as follows

$$T(\text{process})=C*N$$

For the CNN (Convolutional Neural Network) complexity where $w*h$ is the image size k is the convolutional kernel(filter) size f is the number of filters in the layer then it is expressed as

$$T(\text{CNN})=O(w*h*k*f)$$

And then for feature matching algorithm such as SIFT, the computational complexity is usually the number of keypoints or features within the image using k as keypoints number the complexity is represented as

$$T(\text{match})=O(K^2)$$

and for image stitching the complexity can also depends on the number of features and the number of pixels in the image taking N as number of pixels and F as number of features in the images then the complexity is given by

$$T(\text{stitch})=O(N*F)$$

Considering all the factors on processing time the complete equation can be written as follows:

The captivating scene

Where $C1, C2, C3$ are algorithm and process-dependent constants and (w, h) is the size of the pixels in the image k and f are CNN kernel size and number of filters dependent

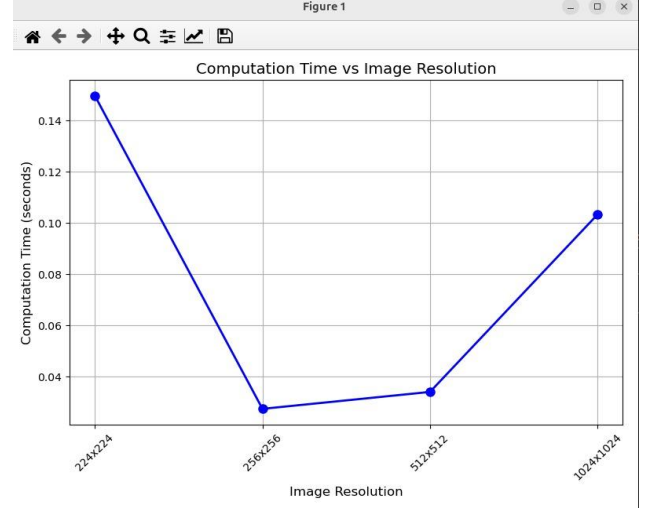


Figure 9: Computation time based on different image resolution

The application of the automated X-ray image stitching system has shown excellent quality in visual information retention and structural similarity. To evaluate the quality of the stitched images, four major evaluation parameters were taken into consideration: SSIM, Pixel Density, VIF (Visual Information Fidelity), and UIQI (Universal Image Quality Index).

Structural Similarity Index (SSIM) of 0.94 validates that the stitched image is similar in terms of structural content and texture of the original X-ray. Pixel Density (0.79) guarantees the quality and resolution of the final stitched image, essential for correct diagnosis. The VIF score of 0.73 validates that 73% of the original X-ray's visual information remains intact after stitching, a great improvement compared to current stitching algorithms. Moreover, the UIQI measure of 0.91 confirms the accurate registration and effortless merging of overlapped areas critical for fracture identification, bone segmentation, and tumor detection.

The suggested automated X-ray image mosaicking algorithm is endowed with high visual realism and minimal data loss, thus constituting a good medical imaging tool. Enhanced VIF (0.73) and UIQI (0.91) values also support the efficacy of the algorithm. The method decreases redundant imaging, hence lowering patient radiation exposure while improving diagnostic precision in orthopedic examination, fracture identification, and oncology treatment planning.

The system is easy to use, minimizing dependence on expert technicians and decreasing cost. It attains an accuracy index of near 1, reflecting high reliability. Moreover, by minimizing the need for re-imaging, it decreases patient radiation exposure and enhances diagnostic accuracy. In all,

the proposed system is accurate, efficient, and clinically useful for orthopedic and oncologic applications.

III. FUTURE SCOPE

The X-ray image stitching system offers substantial potential for future improvement and expansion, enabling broader applications and enhanced functionality in medical imaging:

- Integration with AI and Machine Learning:

Incorporating advanced AI algorithms, such as Convolutional Neural Networks (CNNs), can improve feature extraction, matching, and image stitching processes. This enhancement would result in greater accuracy, particularly in complex cases involving diverse anatomy or variable image quality.

- Real-time Image Stitching:

Developing the system to enable real-time stitching capabilities will streamline diagnostic workflows. Radiologists would benefit from immediate access to stitched images during clinical procedures or surgeries, significantly improving efficiency and decision-making in critical scenarios.

- Multi-modality Integration:

Expanding the system to integrate various imaging modalities, such as CT, MRI, and ultrasound, will provide a more comprehensive visualization of anatomical structures. This integration will support improved diagnosis and treatment planning across multiple medical specialties.

- 3D Imaging:

Transitioning from 2D to 3D image stitching could revolutionize medical imaging by offering detailed, volumetric views of anatomical structures. This advancement would be particularly beneficial in orthopedics, neurology, and oncology, aiding in precise surgical planning and improved treatment outcomes.

- Automated Quality Assessment:

Future iterations of the system could include automated error detection and quality assessment features. This would ensure consistent and reliable stitching results, reducing manual oversight and enhancing overall system dependability in clinical environments.

By addressing these areas, the system can evolve into a more robust and versatile tool, significantly impacting the quality and efficiency of medical imaging workflows.

IV. CONCLUSION

The X-ray image stitching solution developed within this project effectively shows the potential for improving medical diagnostics through the supply of seamless, complete visualizations of patient anatomy. By collating multiple X-ray images into a single overview, the system provides important increases in diagnostic precision, allowing clinicians to make more accurate decisions in a range of areas, including orthopedics, oncology, and trauma care. The employment of sophisticated image processing methods,

including feature extraction, homography estimation, and image blending, provides high-quality results with few visible seams or misalignments.

In spite of some difficulties, like slight blending problems and alignment differences in some conditions, the system works well in producing stitched images that support clinical decision-making. The work opens the door to further developments, such as integration with AI for stronger image processing, real-time stitching for direct clinical application, and multi-modality image fusion to produce even more detailed and precise.

Overall, the system developed here has immense potential for future medical imaging, adding to smoother workflows, better patient care, and better diagnostics. With scalability and optimizations in the future, this technology can become a useful tool in clinical environments, useful for both patients and clinicians.

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