Registration of Medical Images

MRI and Mammography of Breast Cancer

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Abstract

Breast cancer is the most common cancer among women worldwide. For these women, breast conservative surgery combined with radiotherapy has become the standard treatment. However, up to 25% of the cases may have a positive pathologic margin, which results in a high rate of re-operations with their accompanying morbidity and risks. On the other hand, sometimes surgeons may excise considerable amounts of healthy tissue, thus limiting the ability to achieve adequate cosmesis. A method to precisely identify the location and geometry of cancer lesions, considering the specific posture and the image statistics of each individual patient, will provide a much greater probability of a well-planned and successful surgery. This paper represents the research on MRI-Mammogram registration (imaging-based and sensor-based), which is part of an end-to-end framework. We expect that the impact of such a project will be highly significant, including fewer re-operative procedures, minimizing costs, hospitalization days, and surgery complications. [Hoo]

1 Introduction

We propose a non-invasive method for precise cancer analysis to improve surgical success. Our framework focuses on adjusting the patient's posture to ensure accurate tumor removal. This project aims to reduce re-operations, costs, hospitalization days, and surgery complications through an Augmented Reality application.

2 Clinical Background and Motivation

To extend our knowledge about the "scene", we will fuse the whole image information that we will have on hand (e.g., Mammography and MRI), enjoying the best of both worlds while overcoming their weaknesses. For example, one distinct advantage of MRI is its ability to better detect small breast lesions that are sometimes missed on mammograms. MRIs are also more effective in detecting breast cancer in women with dense breasts or breast implants. On the other hand, MRI is prone to more false positive detections than mammograms. Mammograms are an important source of information because they can show calcifications in breast tissue, thus can help in determining whether a specific object is a cancer or not.

Therefore, establishing spatial correspondence between 2D mammograms and volumetric breast MRI scans can help to evaluate and assess different types of breast findings. However, identifying such correspondence is far from being a trivial problem – not only that the images have different contrasts and dimensionality, but they are also acquired under vastly different physical conditions. Moreover, the expected difference between the images is further exacerbated by the effect of mechanical compression of the breast during mammography examination along with the fact that, as opposed to MRI scans, mammograms are projective.

3 Registration

Registration is the process of comparing and contrasting different sets of data that have been captured using separate technologies. In the context of image registration, it involves aligning images to establish a relationship between comparable characteristics. This alignment is achieved by mapping points from one image to corresponding points in another image.

In the specific case of medical imaging, such as MR (Magnetic Resonance) and ultrasound images, registration refers to the process of merging a series of MR images with a 3D ultrasound construct. Before a biopsy procedure, a radiologist segments the MR images and identifies easily recognizable landmarks by placing fiducial points on them.

During the biopsy, a live ultrasound scan generates multiple image segments, which are then combined to create a 3D representation. The fiducial points that were identified earlier are matched to each other. Fusion of the MR images and ultrasound construct is accomplished using a software registration algorithm. This algorithm can be either rigid or non-rigid (elastic) depending on the system being used for fusion biopsy. The specific technique employed for image registration may vary across different fusion biopsy systems.

3.1 Data collection

To gather the data, we captured photographs of individuals assuming various positions. Each person was photographed from five angles: front, left side, right side, back, and stomach. Among these positions, the key ones requiring labeling were "back," "left," and "stomach."

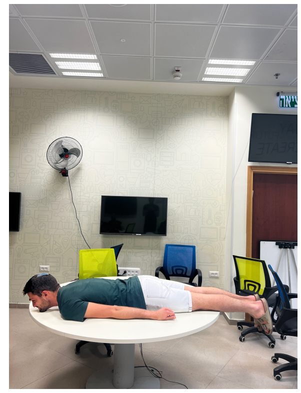
See in Figure 1

After obtaining a substantial amount of data, we supplemented it by incorporating additional images from the internet to get more data. Subsequently, we performed various processing and manipulation techniques on the images to augment the dataset and integrate them into the models.

Initially, we replaced the background with a black backdrop. We then applied ten distinct manipulations to each image, including rotation, salt-pepper noise, flipping, Gaussian noise, cutout (random erasing), elastic transformation, brightening, increased contrast, blur, and mixup augmentation on pairs of images.

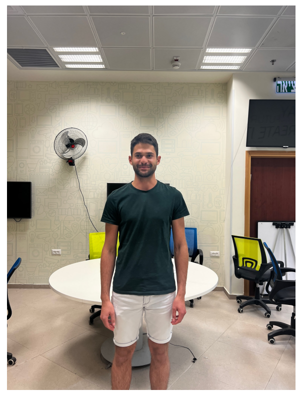
back

left



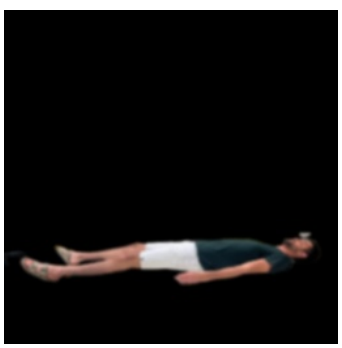
stomach

right

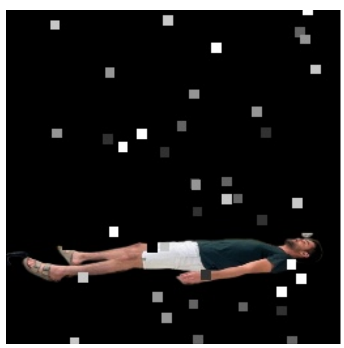


front

Figure 1: Five Different Positions



blurred and flipped



cutout and flipped

gaussian noise and flipped

Figure 2: Manipulations

See Figure 2.

Initially, we had 24 images for each position, and we created an additional 30 images for each, resulting in a total of 720 images for each position. As a result, we now have 1440 images in total to work with.

3.2 Methods

Our research involved the utilization of two key packages: VoxelMorph [Bal+19] and PoseNet [Wig], but eventually, we built our own neural network using the PyTorch library. The primary objective was to explore learning-based image registration using several architectures such as the U-net model. Specifically, we aimed to study the movement between standing and laying positions. To employ the VoxelMorph package, we first needed to preprocess the data. The initial step involved applying an affine transformation to the images. Subsequently, we converted the images into a mask shape, as the VoxelMorph package is specifically designed to work with medical images. In addition to VoxelMorph, we also incorporated PoseNet into our analysis. This package allowed us to accurately detect a person's position within the images, further enhancing our picture analysis capabilities. By combining the capabilities of VoxelMorph and PoseNet, we could gain valuable insights into the transformations between standing and laying positions.

VoxelMorph: A package developed for learning-based image registration, leveraging the U-net CNN architecture.

U-net: This CNN architecture, designed for biomedical image segmentation, has proven to yield more accurate results with less training data. The architecture comprises two stages. The first stage involves the concatenation of convolution, ReLU, and pooling layers to downsample the image. In the second stage, we upsample and merge data from the corresponding level in the downsampling stage. This architecture provides us with valuable spatial information and high-resolution images.

PoseNet: A package that provides multiple state-of-the-art models for running real-time pose detection. See Figure 3.

The method we eventually decided to use is building our own neural network. The neural network we built follows the architecture of four convolution-RelU-max pooling blocks followed by three linear-RelU blocks and a final linear layer that outputs five values representing the affine transformation parameters. We then used the parameters to find the affine transformation matrix and output the transformation parameters and the original input image transformed by the affine matrix. During the training process, we used both real "back" images and "left" images which were transformed into a lying position. We trained our network on both fake and real images as well as the transformation given by the network. Our goal is that the network will output an image that is closest to the "back" image, which will then be used for fine-tuning later.

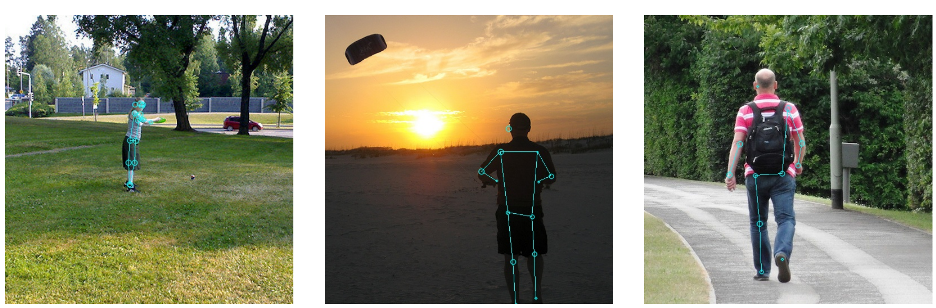


Figure 3: PoseNet Results

Our approach involves a multiscale coarse-to-fine image registration. The first stage is a Coarse – Posture to Posture (P2P) registration, which addresses the significant patient's MRI-Mammogram postures variability. The second stage is a Fine – Lesion to Lesion (L2L) registration, which allows for more accurate and local non-rigid lesion registration, fine-tuning the coarse one.

As part of our research, we attempted to train an Unet model. Due to the fact that we used images without a background and used the MSE function, the results turned out to be bad, so we tried to utilize a pre-trained CNN to classify the output of the Registration Net into two classes - back or left (laying or standing). Since our goal is to register standing into laying, when the result was "left" (standing) we gave the loss "punishment" so that the next calculation would give that mistake more weight and learn to fix it.

4 Results

Initially, our attempts with the VoxelMorph package and the U-net architecture yielded limited success. We also experimented with the PoseNet model in an effort to enhance results; however, this approach proved less effective. Ultimately, the most prosperous approach involved the development of a custom network tailored to the unique dataset we amassed during the course of this research.

The results:

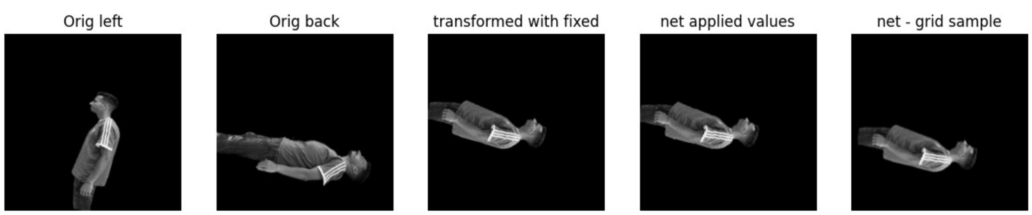


Figure 4: Left to Back Result

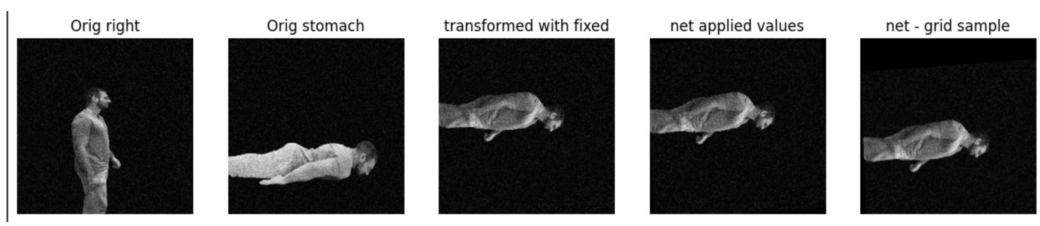


Figure 5: Right to Stomach Result

We compared three types of results.

1. A fixed transformation that rotates the original image by 90 degrees.

2. An image based on the original image that was transformed using the parameters learned by the network.

3. The result image of the network.

We evaluated the outcomes by utilizing the Mean Squared Error (MSE) and the Normalized Cross-Correlation (NCC) to compare them against the original "back" image. Through this comparison conducted on our test set, we determined that the "net-grid sample," as depicted in Figures 4 and 5 above, yielded the most favorable outcomes in terms of both criteria.

5 Discussion

In future endeavors, we can leverage the findings from our current research and apply them to real medical data. The goal would be to develop a specialized tool that can accurately track the movement of objects, specifically lesions, between different positions such as standing, lying on the back, and lying on the stomach.

By using the knowledge gained from the image registration and transformation analysis, we can create a powerful tool that aids in understanding how lesions or other critical features within the medical images shift or change with different patient positions. This could provide valuable insights to medical professionals and researchers, helping them assess the impact of body positioning on disease progression, treatment planning, and patient outcomes.

The combination of VoxelMorph's image registration capabilities and PoseNet's precise person position detection can be harnessed to develop an efficient and accurate tool for medical image analysis. Such a tool has the potential to revolutionize medical imaging practices, providing crucial information for improved diagnosis and treatment strategies.

Author Contributions

- Dr A. Hoogi instructor of this project, conceived the idea.
- T. Seada, L. Breitman, and N. Levine conducted the experiments.

References

[Bal+19] Guha Balakrishnan et al. "VoxelMorph: a learning framework for deformable medical image registration". In: *IEEE transactions on medical imaging* 38.8 (2019), pp. 1788–1800.

[Hoo] PhD Hoogi Assaf. "A 3D Patient-Specific and Posture-Specific Cancer Lesion Model integrated into Augmented Reality to Improve Breast Lumpectomy". In: ().

[Wig] Ross Wightman. *PoseNet Python*. URL: `https://github.com/rwightman/posenet-python`.