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Brain CT Image Registration

AJITH B M[1], IBTISAM PINJAR[2], BHOOMIKA HARDIKAR H V[3], DHEERAJ S[4], REKHA V[5]

[1 2 3 4] Under-Graduate Student, Dept. Of Computer Science and Engineering, Jyothy Institute of Technology, Visvesvaraya Technological University Thataguni Post, Bengaluru-560082, India

[5] Assistant Professor, Dept. Of Computer Science & Engineering Jyothy Institute of Technology, Visvesvaraya Technological University Thataguni Post, Bengaluru-560082, India

ABSTRACT:

Image registration is the process of putting two or more images into the same coordinate system. In the instance of brain CT imaging, image registration can be used to align many CT images of the same patient taken over time or from diverse angles. This might be important for planning surgical procedures, tracking the development of illnesses, and identifying changes in brain structure. There are numerous techniques for image registration, including feature-based and intensity-based techniques. Using techniques that use pixel intensity values and are intensity-based, the best transformation to align the photos is discovered. Intensity-based approaches are typically favored in this situation due to the fact that the brain CT images have few distinguishable characteristics and the structures of interest have similar intensities. A popular method for determining how similar two images is to use their mutual information. Mutual information, which is insensitive to changes in intensity, is used to determine information is shared between two images.

Key Words: Deep Learning techniques; Image Registration; Intensity; Feature;

INTRODUCTION

Image registration is the process of overlaying pictures for analysis, and it's a crucial stage when information from several pictures that might have been taken at different times, from different angles, and with different sensors must be merged. When studying data from the human brain, it is frequently interesting to understand the connection between brain shape and function. Registration in medical imaging enables the fusion of data from several modalities, such as CT, to provide a complete picture of the patient. For the categorization process, dicom photos from the dataset are transformed into png format. To extract similar images from the provided dataset, the sinogram images are categorised based on the features. In this manner, we obtain the altered sensed image, which is then visually convincingly placed on the reference image. By aligning the intensities of the images, intensity-based registration can enhance the accuracy of subsequent analysis or comparisons.

LITERATURE SURVEY

[1] Computerized Image Registration techniques, according to the author J. B. Antoine Maintz (2012), can enable automatic and accurate image alignments without a lot of user input and provide tools for visualizing combined images. This study's objective is to provide a review of works on medical image registration. This paper provides a thorough overview of image registration techniques and the uses for them. The paper serves as an overview for those already working in the subject, an introduction for those just entering it, and a resource for those looking for literature on a particular application. Methods are categorized based on the many elements of medical image registration.

[2] In this paper, it provides a preprocessing stage for an automated volumetric CT stroke picture diagnosis system, according to the author Kalaivani Chellappan(2015). It deals with the automatic intensity-based 3D image registration of CT angiography (CTA) and dynamic CT (used for CT perfusion imaging) images. Since the gantry tilt was used to acquire the dynamic CT images, the correct geometry was discovered. Implicit tilt correction occurs together with intensity-based registration of the CTA image. The segmented skull overlaps from both images act as a barometer for the accuracy of image registration. The results are promising, and future application will have a greater impact on clinical viability.

[3] An important stage in the automated interpretation of brain computed tomography (CT) images of patients with acute cerebrovascular disease (ACVD), according to the author Hongmei Yuan (2021), is image registration. However, due to the significant inter-subject anatomical variability, low resolution of soft tissues, and high computational costs, conducting brain CT registration reliably and quickly remains extremely difficult.

[4] Image registration is an essential task in many medical image analysis applications, claims the author Andres Diaz-Pinto (2021). Deep learning has significantly improved algorithmic performance for a variety of computer vision tasks, including medical picture registration, in recent years. The creation of deep learning-based medical image registration algorithms has dramatically increased during the past few years.

Therefore, it is appropriate and required to do a thorough analysis of the most cutting-edge algorithms currently available in the industry. This study aims to comprehend the clinical applications and difficulties that led to this breakthrough, analyze the usefulness and constraints of current treatments, and offer insights into open problems and unmet clinical needs that may influence future research directions.

[5] The author Hamid Reza Boveiri(2020) claims that image-guided therapies are saving the lives of many patients, and that the picture registration problem is in fact the most challenging and complicated topic to solve. On the other hand, recent significant advancements in machine learning, including the ability to deploy deep neural networks on modern many-core GPUs, have created a prospective opportunity for challenging a variety of medical applications, including registration. This article presents a thorough analysis of the most recent research on medical picture registration using deep neural networks.

[6] Image registration is a crucial step in the applications of numerous medical image analysis, claims the author Subrato Bharati (2022). Deep learning (DL)-based medical image registration models have seen a phenomenal increase in development in recent years. This paper offers a thorough analysis of medical image registration. First, supervised registration categories such as completely supervised, dual supervised, and weakly supervised registration are discussed. Then, as a part of unsupervised registration, similarity-based and generative adversarial network (GAN)-based registration is described.

[7] Deformable image registration is crucial for medical image analysis, claims author Yongning Lu(2013)[7]. Due to the intricacy of modelling the link between two images, multi-modal image registration continues to be a difficult study area. Although mutual information (MI) is frequently employed in the field of multi-modal picture registration, it has drawbacks such statistical inadequacy and/or interpolation artefacts.
When bias field and noise are present, the issue gets worse. Before image registration, there have been attempts to map images to a common modality, but the mistake provided by the mapping may be deleterious to the registration

[8] According to Natan Andrade Fabio A. (2018), a new, intriguing, and unexplored world for image registration area is made possible by the wide range of medical image modalities (such as Computed Tomography, Magnetic Resonance Imaging, and Positron Emission Tomography) acquired from the same body region of a patient as well as recent advancements in computer architectures with faster and larger CPUs and GPUs. Understanding the etiology of diseases, improving surgery planning and execution, detecting otherwise undiscovered health problem signals, and mapping brain capabilities are all made feasible by precise and accurate picture registration.

[9] The author Prathima Devadas (2020), claims that in modern times, people are more susceptible to numerous ailments that can be efficiently recognised through scans. In the earlier works, mammography pictures were subjected to the intensity-based image registration. In this study, brain MRI (Magnetic Resonance Imaging) images, which are routinely used among persons with any type of brain illness, are used to evaluate the intensity-based image registration. The technique of identifying an image's distortion from its original structure is known as image registration. Intensity-based registration is utilised to streamline the process for patients and eliminate the need for human intervention. Various metrics and techniques, ranging from local transformations to global transformations, are used to conduct picture registration.

[10] According to Shu-Kai S(2010), on Image registration, it makes sense to align images by matching related pixels that are idealistically thought of as the same on an overlapping region. This idea serves as the foundation for the method of picture registration that is suggested in the current study, which applies the information theorem to the related intensity data. The histogram of the intensity differences serves as the foundation for an objective function based on entropy. On the overlapped region, intensity differences show the variations in the relevant pixels between the referenced and sensed images.

LITERATURE SURVEY TABLE

Papers	Year of publication	Methodology and approaches	Gaps
[1]	**2012** **Authors-** **J. B. Antoine Maintz, Max A. Viergever**	**The paper provides a thorough overview of the different techniques used in medical image registration, including feature-based methods, intensity-based methods, and hybrid approaches. Each technique is explained in detail, highlighting its strengths, limitations, and suitable applications.**	**The drawback is it was supposed to classify the grayscale image into different classes of pixels that are segmented priory by the userfrom the reference image which was a time-consuming and complex process.**

[2]	**2015** **Authors-** **Israna Hossain Arka, Kalaivani Chellappan, Shahizon Azura Mukari, Zhe Kang Law, Ramesh Sahathevan, Ashrani Aizzuddin Abd. Rahni**	**The method for removing the tilt artefact, which happens when the patient's head is inclined during imaging, is described in the publication. The technique seeks to correct the tilt and bring the images' anatomical alignment back.**	**The difficulty and potential inaccuracies involved in precisely calculating and correcting the tilt angle are a significant downside of tilt correction in medical imaging. Patient placement, scanner alignment, or motion during image acquisition, might cause tilt artefacts.**
[3]	**2020** **Authors- Hongmei Yuan, Minglei Yang, Shan Qian, Wenxin Wang, Xiaotian Jia & Feng Huang**	**To obtain precise alignment of brain CT images, the hybrid approach combines supervised learning with conventional registration approaches. The dissimilarity between the registered and target images is measured using a loss function, which directs the training of the CNN model.**	**This method's biggest downside might be the need for a lot of annotated training data. Supervised learning techniques like CNNs often need a sizable dataset with precise ground truth registration data.**
[4]	**2021** **Authors- Xiang Chen, Andres Diaz-Pinto, Nishant Ravikumar and Alejandro F Frang**	**The research explores different deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and generative adversarial networks (GANs), that are used to medical picture registration.**	**GANs are infamous for their training instability, which makes it difficult to attain convergence and consistently produce high-quality results.Mode collapse, where the generator only generates a small number of constrained and repeated samples, can affect GANs and prevent them from fully capturing the diversity of the training data.**
[5]	**2020** **Authors- Hamid Reza Boveiri, Raouf Khayami, Reza Javidan, Ali Reza MehdiZadeh**	**The paper addresses different DNN designs, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures, used in medical picture registration. These designs are made to collect spatial data and develop intricate picture mappings.**	**They have developed industrial corporate level of laminographic pictures whereintensity of artifacts is more. Methodology tried to remove artifacts using back projectionfiltration.**
[6]	**2022** **Authors- Subrato Bharati, M. Rubaiyat Hossain Mondal, Prajoy Podder, V. B. Surya Prasath**	**This paper offers a thorough analysis of medical image registration. supervised, dual supervised, and weakly supervised registration are discussed. Then, as a part of unsupervised registration, similarity-based and generative adversarial network (GAN)-based registration are described.**	**Variance is reduced and costof introducing bias. Negativity constraint cannot be used.**
[7]	**2013** **Authors- Yongning** **Lu, Ying Sun,** **Rui Liao,** **Sim Heng Ong**	**The paper proposes a novel similarity metric based on intensity matching information, which can be learned from the already registered training pairs or image pairings that are registered by using MI based registration. This method avoids explicitly mapping the images to a common modality.**	**To perform cross validation, Different oriented images arerequired. Mean square Error is required to underfit and overfit the data.**
[8]	**2018** **Authors- Natan Andrade Fabio A. Faria Fábio A.M. Cappabianco**	**The purpose of this paper is to provide an overview of the state-of-the-art in medical image registration, beginning with preprocessing procedures, covering the most widely used approaches in the literature, and concluding with more recent advancements and views from the use of Deep Learning architectures.**	**Recurrent Neural Networkis slow to use. The trainingdataset is high and iteration takes lot of time**

[9]	**2020** **Authors- Prathima Devadas, G.Kalaiarasi, M.Selvi**	**The metrics are assessed using the Affine, Demons, and Hybrid (Affine + B-Spline) registration techniques. The effective image registration algorithm for brain MRI images is thought to be the approach that produces images with a higher degree of similarity**	**In each reconstruction iteration, Noise has to be removed simultaneously for under sampled data. Sincesampled data used is less, Itis not sure about applicationfor complex data.**
[10]	**2010** **Authors- Shu-Kai S. Fan, Yu-Chiang Chuang**	**On the overlapped region, intensity differences show the variations in the pixels between the referenced and sensed images. By minimizing the entropy of differences and iteratively updating the parameters of the similarity transformation.**	**Uncertain differencesbetween actual images that is present and reconstructed images. Multiple prior images are required to train and registered images.**

Methodology

The approach under consideration seeks to create a useful image registration method specifically for brain CT images. In medical imaging, aligning and superimposing photographs of the same structure from several time periods or imaging modalities is known as image registration. To accurately align brain CT images, our system focuses on intensity-based and feature-based registration techniques.

Data description: A dataset of brain CT pictures is used by the system, and it consists of brain CT images. The dataset offers a wide range of picture features and registration issues because it consists of numerous instances and both normal and pathological brain CT images.

Intensity based: To align brain CT scans based on the similarity of their intensity values, the system uses intensity-based registration approaches. It makes use of a reliable optimization technique and a statistic, like mutual information, to assess how similar two photos are. The intensity-based registration method maximizes the similarity metric to guarantee precise alignment.

Feature based: Brain CT images are aligned by the system using feature-based registration techniques based on important picture attributes. It takes out important details from the photos, like corners or key-points, then compares those details between the images. In order to align the images, the registration step requires estimating a transformation model based on the matched characteristics.

Performance evaluation: The system uses a number of evaluation measures to compare how well intensity-based and feature-based registration work. Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and feature matching accuracy are some of these measurements. These metrics include numerical evaluations of feature correspondence, image quality, and registration accuracy.

Comparative analysis: The intensity-based and feature-based registration techniques are compared by the system. It assesses how well they perform in terms of precision, robustness, computing effectiveness, and capacity for handling various kinds of brain CT images. The examination sheds light on each method's advantages and disadvantages.

Implementation

In the first step of the registration process, features from the input image and a collection of images are extracted using the ResNet50 model. The features are analysed to get the dataset image that is the most comparable. The feature-based method for feature-based image registration makes use of ResNet50 for global feature extraction and ORB for local feature detection and matching. SimpleITK is used by the intensity-based approach to do registration based on intensity. It confirms that the size of the input and comparable photos is compatible before converting them to grayscale. If necessary, the comparable image is resized to match the supplied image.

The abundance of pictures makes it easier to record the variety of brain CT scans, including various anatomical structures, diseases, and intensity distributions.

Choosing an appropriate similarity metric, such as mutual information or normalised correlation, is necessary to calculate the degree of similarity between the input image and related images. The system also chooses a transformation model, such as rigid or affine, to define the spatial mapping between the pictures. Using an optimization's strategy like gradient descent, the transformation parameters are adjusted iteratively.

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