The Advantages of MIT MRI Algorithm

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Abstract

Magnetic resonance imaging (MRI) is a non-invasive imaging technique used to compute three-dimensional, detailed images of the structure and the physical processes of the body without the use of damaging ionizing radiation. Today's medical imaging algorithms provide a solution, but in a slow manner. MIT VoxelMorph machine learning algorithm, as opposed to other medical imaging algorithms, like segmentation, offers a more efficient way to speed up MRI, benefiting the patients. VoxelMorph implements a CNN and spatial transformer to train itself while registering thousands of pairs of MRI images. The spatial transformer enables the algorithm to reconstruct one image from another while learning information about each group of voxels. This information is used to calculate parameters that can be applied to any other scan. Segmentation optimizes each pair of images independently, without a spatial transformer. Segmentation lacks the innovation due to the fact it does not follow a novel registration method, making the algorithm time consuming and inefficient. VoxelMorph can greatly benefit the medical community because of the ability to register scans 1000 times faster than the traditional systems. Yet, the algorithm will most likely not be implemented anytime soon due to many social factors.

The Advantages of MIT MRI Algorithm

Introduction

Medical imaging has completely revolutionized the medical field. Magnetic resonance imaging (MRI) is an important technique in the medical field because the process allows medical physicians to generate images of organs in the body. MRI enables physicians to find damaged soft tissue without the need for extensive surgery. Detection of damaged tissue in the brain can result in early detection and intervention for several brain diseases. An important problem with traditional medical imaging registration is the time it takes to analyze and compare images. Traditional methods of newer medical imaging algorithms over time have slightly made MRI's more efficient, but most of them are still cumbersome. MIT VoxelMorph machine learning algorithm, as opposed to other medical imaging algorithms, like segmentation, offers a more efficient way to speed up MRI's, benefiting the patients. Existing algorithms start from scratch for every pair of images. VoxelMorph speeds the process up by learning as it registers medical images. Segmentation methods are usually designed to bring more accurate results, making medical imaging process time consuming. As mentioned in "An Unsupervised Learning Model for Deformable Medical Image Registration" written by the developers of VoxelMorph, the algorithm will benefit many applications in the medical field. Faster medical resonance imaging is critical for capturing dynamic activity in the brain. VoxelMorph will benefit the patient because the algorithm is able to pick up missed information. It is important to first understand how magnetic resonance imaging works and its importance in the medical field.

Background

The medical field has benefited from the rapid development of global technology; medical imaging has improved early detection and treatment of disease while offering no side effects to the patient. As mentioned in McPhail and colleagues' paper on MRI, the authors state that "The development of magnetic resonance imaging (MRI) for use in medical investigation has provided a huge forward leap in the field of diagnosis, particularly with avoidance of exposure to potentially dangerous ionizing radiation" (McPhail, Tognarelli, Mary, Cox, Robinson, & Vijay. 2015, p 1). Figure 1 illustrates an image of a brain that was registered by an MRI (McPhail, Tognarelli, Mary, Cox, Robinson, & Vijay. 2015, p.5). MRI images

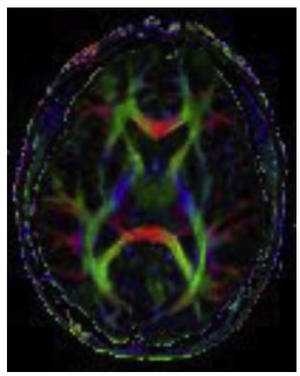

Figure 1. MRI image.

provide detail information on certain structures of the body without the need of surgery. Different MRI algorithms over time have mitigated the process of image registration, MIT VoxelMorph validates a solution to the common problem of current MRI algorithms.

VoxelMorph is a fast machine learning algorithm developed by five MIT graduate students. The algorithm can register brain MR scans and other 3D images more than 1000 times faster than traditional medical imaging algorithms. Traditional medical image registration methods optimize an objective function for each image. VoxelMorph speeds up the process of imaging by learning as it registers images. The machine learning algorithm learns how to align these images and estimates parameters on alignment. The algorithm then uses these parameters to map all pixels of one image to another (Balakrishnan, Zhao, Sabuncu, Guttag, & Dalca, 2018, p.1-3). The VoxelMorph algorithm has a wide range of potential application in the medical field. Today's medical practices use the current norm of MRI algorithms. These old algorithms are reliable, but they are an inefficient solution compared to today's current technology.

Incorporating the VoxelMorph algorithm into medical practices will greatly improve the prognosis of patients worldwide, although applying a brand-new technology is quite difficult. Implementing VoxelMorph throughout hospitals, clinics, and practices will require time, money, and resources that may be unavailable. Training physicians to switch from the norm to the new technology will be time consuming and may cause more harm than benefit to the patient in the short run due to the increase in error of a new technology. Therefore, the current norm of MRI algorithms will most likely stay the current norm. These outdated algorithms lack the innovation VoxelMorph contains. The segmentation algorithm is a popular algorithm used today in medical practices, although it lacks the same efficiency as VoxelMorph.

Precedents & Related Work

Advancements in medical imaging have provided large amounts of data with an increasingly high level of quality. The analysis of large and complex medical images is a dull and intricate task for physicians, who must manually extract important information. Manual image analysis is often time consuming and susceptible to errors. Computerized methods have led the path to automatic medical imaging. Image Segmentation is a commonly used tool for medical image analysis. Segmentation can be grouped into several methods, such as manual, intensity-based, atlas-based, surface-based, and hybrid segmentation methods. Most of these methods are outdated, however, some are efficient in certain fields. According to research done by Despotović, Goossens, and Philips (2004), newer segmentation methods are designed to bring more accurate results by implementing three-dimensional neighborhood information from plot maps. MRI segmentation is used for computing and imaging different structures, which can help discover lesions and damaged tissue in the brain (Despotović, Goossens, & Philips, 2004, p.1, p.3). Segmentation for MRIs are a general problem in medical image analysis due to the increase in time consumption when computing precise results. Segmentation can take anywhere from 30 minutes to hours depending on the size of structure, while also being prone to errors. As a clinician, it is viable to have critical patient information that is accurate and timely. Segmentation is not the correct algorithm to use when dealing with the outcome of patients' lives because there are much better alternatives. It is important to understand what makes MRI such a complicated and daunting procedure.

Support

VoxelMorph

Physicians often need to compare two MRI images to track changes in the body over a period of time. This process can be significantly simplified by the MIT VoxelMorph algorithm. The algorithm follows a novel registration method, compared to segmentation that follows a more deformable registration method. A novel registration method learns "a parametrized registration function from a collection of volumes" (Balakrishnan, Zhao, Sabuncu, Guttag, & Dalca, 2018, p.1). The volume is made up of 3D pixels, known as voxels, that are aligned when compared with two images. Figure 2 illustrates two image pairs and the velocity field of the pair of images (Dalca, Balakrishnan, Guttag, & Sabuncu, (2018), p.3).

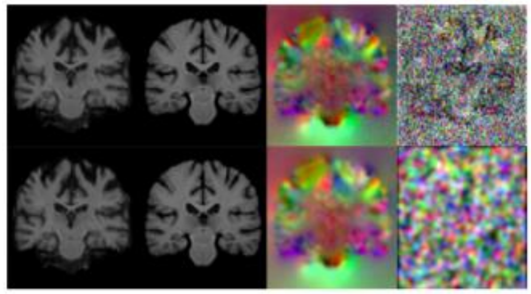

Figure 2. Image pair.

MRI images contain a massive amount of fixed 2D images while a volume is a massive 3D rendering of these images. VoxelMorph sifts through millions of voxels in an efficient and quick manner, then assigns them into a unified 3D image. Other medical imaging algorithms follow a more deformable registration method that requires an intensive amount of computing power. A deformable registration method aligns each voxel with a similar voxel in order to create a pair. The registration mapping of these pairs can take up to hundreds of hours since the method is limited to mapping two voxels at a time. After each registration, the method dismisses all data containing each voxel location. The method starts from scratch each time it registers new pairs; VoxelMorph follows a novel registration method that lets it learn while registering thousands of pairs of images.

The VoxelMorph algorithm takes in two image volumes as parameters, F and M. These two 2D images may be brain scans, where M, the moving image is positioned onto F, the fixed image. The function $g\theta(F, M) = \varphi$ uses a convolutional neural network (CNN) where φ is a registration field and θ are learnable parameters of g (Balakrishnan, Zhao, Sabuncu, Guttag, & Dalca, 2018, p.3). The function takes in F and M, the two 2D images and positions M over F to create a 3D volume. Figure 3 illustrates how the algorithm works (Balakrishnan, Zhao, Sabuncu, Guttag, & Dalca, 2018, p.2).

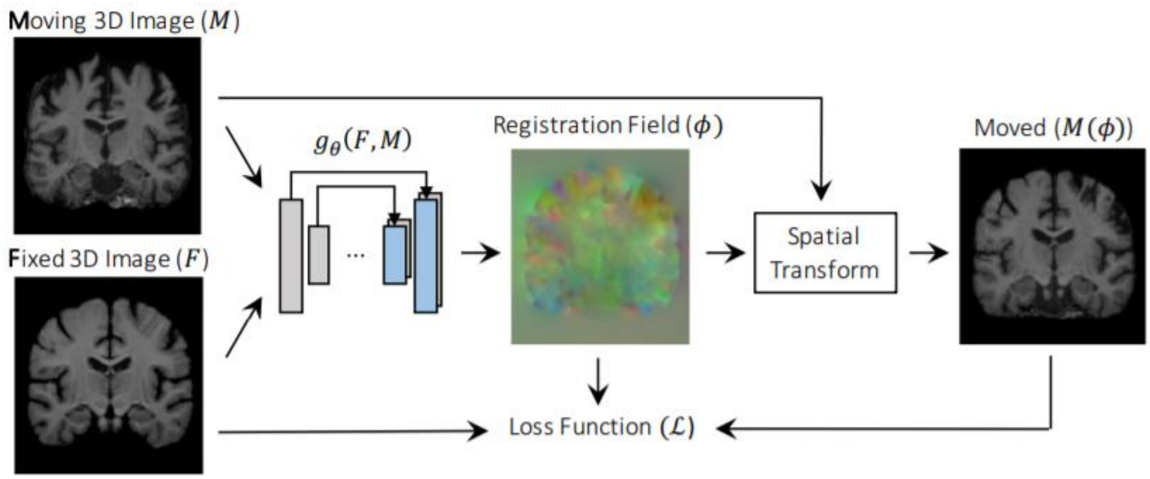

Figure 3. Overview of the VoxelMorph algorithm.

CNN is commonly applied to analyzing visual imagery and image processing. The VoxelMorph CNN component gains the necessary information needed during training. The CNN component enables the algorithm to be able to execute one computable function during each registration. An Additional algorithm may be needed to compute accurate image registration when implementing a CNN component. VoxelMorph, however, does not require additional information beyond image data. The function g generates φ by implementing an encoder and decoders on F and M. The combination of an encoder-decoder helps map raw image pixels into a rich representation of a collection of vectors. With the combination of thousands of vectors, the algorithm computes a final registration field φ. VoxelMorph also implements a modified computation layer called a spatial transformer.

VoxelMorph implements a spatial transformation function in order to use a standard gradient based method to find the minimum difference between M(φ) and F (Balakrishnan, Zhao, Sabuncu, Guttag, & Dalca, 2018, p.4). A spatial transformation defines a relationship between each pixel in the input and output images. The algorithm uses a differentiable function that lets the algorithm use a standard, gradient-based method grounded on spatial transformer networks to compute M(φ), the moved image of M. The differentiable function takes in effects for each voxel and computes a subpixel voxel location in the image M. The spatial transformer enables the algorithm to capture similarities of voxels in one MRI image with other voxels in another image. The algorithm can learn information about each group of voxels, enabling it to optimize future parameters for later scan pairs. Other medical imaging methods like segmentation are not as efficient as VoxelMorph since the algorithm does not incorporate a novel registration method.

Segmentation

Just like VoxelMorph, segmentation also follows a CNN component, but assigns a label to each voxel. Labeling each voxel dedicates more time to the run time of the algorithm, therefore decreasing efficiency. Segmentation of 3D images works by slicing each image and segmenting it individually in a slice-by-slice manner. This process "requires a postprocessing step to connect segmented 2D slices into a 3D volume or a continuous surface" (Despotović, Goossens, & Philips, 2004, p.1). The dependence of another algorithm causes a decrease in efficiency that VoxelMorph avoids. The segmentation of 2D images is reliable due to the lack of complexity, but segmentation of 3D images may contain nonsmoothed surfaces and inconsistencies due to omitting important structural data in 3D space. Segmentation does not implement a spatial transformer, unlike VoxelMorph. Therefore, disabling "neural networks to perform both global parametric 2D image alignment and spatial transformations" (Balakrishnan, Zhao, Sabuncu, Guttag, & Dalca, 2018, p.3). Segmentation is an extremely outdated method for medical imaging due to its limitations.

The segmentation method defines an image as a function with two to three parameters depending on the type of space. A 2D space, I(*i*, *j*) takes in two parameters, known as pixels, and a 3D function, I(*i*, *j*, *k)* takes in three voxels. The parameters of both 2D and 3D take in *i*, the image column and *j*, the row number, while 3D also take in *k*, the slice number. Each image element consists of the parameters and a unique intensity value that is determined by the average magnetic resonance characteristics (Despotović, Goossens, & Philips, 2004, p.5). Figure 4 illustrates the segmentation method described by Despotović, Goossens, and Philips (2004) on page 4 of there paper. An image pixel (*i*, *j*) is represented with the single square in the 2D image slice while there is a voxel (*i*, *j*,*k*) representing the group of cubes in the 3D image.

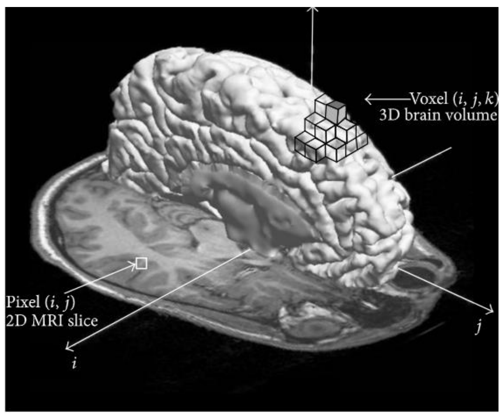

Figure 4. Segmentation of the brain.

Segmentation model must compute each pair individually; the model must sift and assign through millions of voxels into a unified 3D image. The process of aligning all voxels is time consuming since the method is simply placing two different images on top of each other until one fits the other. Segmentation lacks the learning capabilities that VoxelMorph implements. According to the research by Despotović, Goossens, and Philips (2004), VoxelMorph retains all data pertaining to every voxel location and learns from each registration. VoxelMorph can redefine medical imaging if given the opportunity to be implemented in medical practices across the world.

Social Impact

Current medical imaging only allows an image to be registered hours after an operation. Instating VoxelMoprh could allow image registration during operations, which could greatly benefit the outcome for the patient. For example, when resecting a brain tumor, surgeons might need to scan the patient brain before and after the surgery to confirm if the tumor was completely removed. A common problem in this case is that these surgeons may miss a small part of the tumor and will need to go back into the operating room hours later. This process is prolonged not only for the surgeons, but for the patient as well. With VoxelMorph, surgeons could potentially register images in real-time without the need to continuously check back and forth for surgical errors. The algorithm enables surgeons to have a faster operation by cutting down the time it would usually take to register images with the traditional methods. In figure 5, the process of MRI was able to properly determine where a tumor was in this patients' brain (Isin, Direkoglu, & Sah, 2016, p.3).

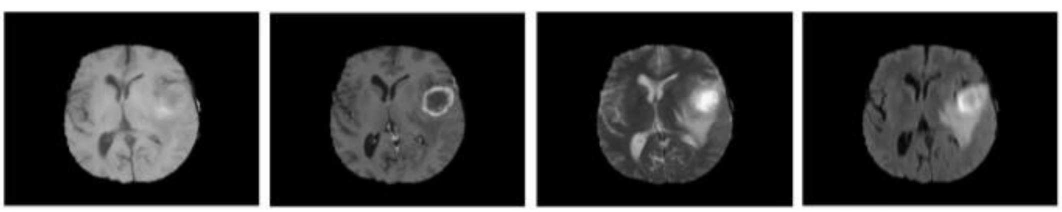

Figure 5. Brain tumor.

The implementation of VoxelMorph worldwide will make a quantitative change of image registration from hours to seconds, opening the door to new possibilities. These possibilities range from running the algorithm during an MRI scan, while a patient is still in the scanner, to permitting clinical decision making about what types of data needs to be collected. The implementation of VoxelMoprh will not force the patient to come back days or weeks later for critical information. The Harvard graduate, Daniel Kraft talks about how new technologies are changing the medical field.

In the Ted Talk “How are technologies converging to drive medical progress,” Daniel Kraft talks about the change in the medical field which was brought upon by the advancement of technology. Daniel has published multiple articles on the future of the medical field while also serving as the founder and chair of Exponential Medicine, and faculty chair for medicine and neuroscience of Singularity University. During his Ted Tall, Daniel raises the question, “What was once a luxury in the past is now the norm” (Kraft, 2007, 2:10). He states that the redevelopment of the medical field will allow the opportunity to redesign, rethink, and are define medicine. Although VoxelMorph can greatly benefit and help revolutionize the medical field, it will most likely not be implemented due to the potentially risks it poses for society. Implementing an unfamiliar technology into medical practices can cause confusion and error. The journalist Eliza Strickland raises the question on why most superior new technologies are not implemented into the medical field.

The researchers of VoxelMoprh accurately tested their algorithm on 250 test brain scans in only two minutes with a traditional central processing unit. The algorithm was able to correctly register all 250 test cases in only one second using a graphics processing unit (Balakrishnan, Zhao, Sabuncu, Guttag, & Dalca, 2018, p.6). Although the algorithm can clearly benefit many applications, the medical field will most likely never see its full potential. With the growing presence of artificial intelligence, the medical field is prime for new efficient algorithms that could change lives. In Eliza Strickland’s magazine article “Making Medical AI Trustworthy,” the author raises the question “why most of the new algorithms don’t make it into their way into hospitals and clinics?” (Strickland, 2018). Eliza graduated Columbia University with a Master's in Journalism and Bachelors of English from Tufts University. The journalist published multiple articles on the future of the medical field. An introduction to a new technology can be intimidating. Applying VoxelMorph throughout hospitals, clinics, and practices will require time, money, and resources that may be unavailable. Strickland states that humans simply do not trust new technology. Without solid reasoning that a new technology will work as efficiently as the current, people will most likely stick to the norm. In order to change from the current standard MRI algorithm to VoxelMorph, there will be a requirement for new infrastructure and training for prevention of errors. If given the opportunity, VoxelMorph can make a drastic social impact in the medical field, for both patients and physicians. From an ethical standpoint, the philosopher John Stuart Mill might believe that VoxelMorph should be implemented because of his beliefs.

From an ethical standpoint, the philosopher John Stuart Mill's belief of utilitarianism can be applied to the implementation of VoxelMorph. The principle states that actions are right when they promote overall human happiness. Instead of focusing on the rights or ethical implication of an action, a utilitarianism may focus on the consequences of the actions instead. As discussed earlier, the implementation of VoxelMorph in medical practices worldwide will decrease the amount of errors in surgery by missing a portion of the tumor. The implementation of VoxelMoprh will allow for instant critical information to patients without the need to come back weeks or days later. Mills might claim that VoxelMorph should be implemented throughout medical practices worldwide because of the increase in happiness that the algorithm will provide to patients and physicians. Even though the implementation might take time and resources that a lot of medical practices don't have. Mills however might disregard the negative consequences. A person with deontological beliefs may also agree with a utilitarianism because of their own perspective.

A deontologist does not focus on the consequences of an action like a utilitarianism might. Instead, a deontology is an ethical theory that uses rules to distinguish right from wrong. The philosopher Immanuel Kant believed that ethical actions must be followed by moral laws. Kant might claim that the implementation of VoxelMorph into medical practices will be right, because a deontologist does not require weighing the costs and benefits of a situation. Kant might choose to avoid subjectivity and uncertainty because of the principle of simply following a set of rules. Kant belief of following a universal moral law will require medical practices to do the moral action and choose to implement VoxelMorph without the possible consequences. Both Kant and Mills ethical beliefs imply that it is right to incorporate VoxelMorph into medical practices, yet their possible consequences that ethicist might ignore.

Conclusion

MRI is becoming more prevalent in clinical practices. The advancement of technology over the last decade have led to serious changes in medical imaging. Today’s traditional systems take hours to register and scan images. VoxelMorph could potentially change the current norm of medical imaging. The algorithm developed by MIT graduate students works by learning while registering thousands of pairs of images. VoxelMorph implements a novel registration method that follows a deformable method. Adapting a novel registration method enables the algorithm to learn while registering images, making the algorithm 1000 times quicker than segmentation. Both segmentation and VoxelMorph are powered by a CNN component that processes images across layers of computation. Segmentation slows down the CNN component by labeling each individual layer. Labeling requires more computational power and increases the run time of algorithm. The presence of spatial transformers in VoxelMorph allows the algorithm to learn information about groups of voxels during each scan. VoxelMorph uses spatial transformers to calculate optimal parameters that can be applied to any scan pair. Implementing VoxelMorph worldwide can clearly change the medical imaging field. The decrease in runtime would not only benefit the professional, but also the prognosis of the patient.

The VoxelMorph algorithm, as opposed to segmentation, offers a better alternative to medical imaging. Therefore, creating a better patient diagnosis outcome and a better MRI experience. Although the benefits of implementing VoxelMorph significantly outweighs the negative impacts, physicians will most likely never be able to test the algorithm in real-world settings. Patients will still have to wait hours to days to hear back with critical information that they have the right to know immediately. VoxelMorph can greatly benefit patients by providing quick MRI image registrations, due to the lack of trust from the medical community, the algorithm may never see the light of day. VoxelMorph should indeed be implemented in all medical practices because of the obvious positive reasons. The medical field is relativity new and has only been rapidly growing in the past decade because of the continuous advancements of technology. With patience, patients and physicians will see the benefits of VoxelMorph one day.

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