UNIVERSITY OF ST ANDREWS

A COURSE WORK ON STRUCTURED LIGHTING

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INTRODUCTION

Medical Imaging plays a vital role in many areas of medicine, including diagnosis of diseases, treatment planning, and monitoring of response to therapy, and overall, facilitate clinical decision [1]. However, to achieve this purpose, imaging systems are designed to maximized image quality. Given the inherent complexity of the human body and the diversity of possible states of diseases, several biomedical imaging modalities, including the X-ray, Computed tomography (CT) scans, Magnetic resonance imaging (MRI), and ultrasounds (US), have been adopted for clinical use. Although these imaging modalities offers numerous advantages or benefits in clinical practices, they are faced with several challenges. One of these challenges is the high risk associated with these modalities. For example, X-rays and CT scans use ionizing radiation in their image construction process, which may lead to an increased risk of cancer [2] when exposed to the patient body cells**.** Also, non-ionizing radiation in MRI generates heat within the body, resulting in thermal injuries in some case [3]**.** Another challenge is data acquisition time. Patients are not static objects, and motion during the image formation process can create artefacts that reduce image quality. Although increasing imaging speed can reduce the patient's motion, there is a need for sufficient data to achieve adequate image quality, which is limited.

To address these challenges, the compressed sensing approach for image reconstruction has attracted tremendous attention in biomedical imaging because of its benefits to enable image reconstruction with high quality, reduced radiation dose and more, from fewer data samples [1, 4]

This section focuses on the application of the compressed sensing-based approach in biomedical imaging to reconstruct images with good quality.

- **Compressed Sensing in Magnetic Resonance Imaging (MRI)**

Magnetic resonance imaging (MRI) is a non-invasive radiology imaging technique use to visualize the anatomical and physiological properties of many organs of the body using magnetic fields and radio waves [5]**.** It has been widely used in radiological diagnosis due to its high spatial resolution, non-invasive and non-ionizing radiation metrics. In order to acquire a spatial resolution image with a high signal to noise ratio using MRI, the image is acquired with more K-space data.This, in turn, increases acquisition time which may introduce several problems, including increased in motion artefacts, especially for patients with control problems and moving organs [6].

Compressed sensing technique offers an advantage in MRI for accelerating MRI acquisition time by using fewer K-space data, to reconstruct images with high quality, which benefits both patients and healthcare economics. MRI obeys two key requirements for the successful application of compressed sensing-based approach [7], which includes;

I. Medical imaging is compressible by sparse coding in an appropriate transform domain.
II. MRI scanners naturally acquire encoded samples rather than the direct pixel value of samples**.**

Despite the advantages of applying compressed sensing to MRI, it comes with some disadvantages, including low computation speed with large accelerating factor [6]**.** The reason for this is because the reconstruction of MRI imaging using a compressed sensing approach requires solving an under-determined linear problem.

- **Compressed Sensing in Computed Tomography (CT)**

Computed tomography (CT) is a non-invasive imaging modality extensively used clinically to evaluate patients with various conditions. However, CT scans expose patients to a high dose of X-ray radiation, resulting in increased lifetime risk of cancer [2].

Compressed sensing technique has attracted huge attention in both CT and micro CT community [8]**.** Several studies using compressed sensing algorithm have been employed in the reconstruction of CT images. However, the total-variation based algorithm has shown remarkable progress in CT image reconstruction with only a few X-ray projection and fewer dataset [9, 10]. This produces CT images with high quality, and also, reduces the risk of cancer.

One major disadvantage of this approach is that it causes CT image regions of low contrast to be over smoothed [11].

- **Compressed Sensing in Ultra Sound**

Ultrasound (US) imaging is one of the medical imaging modalities used in clinical diagnostics diagnosis, mainly in cardiology, ophthalmology, urology, and other areas [12]. Its wide usage is due to its low cost, real-time, safety and rapidity. Ultrasound uses sound wave to reproduce images inside of the body. Despite its numerous advantages in clinical diagnostics and other areas, current challenges in acquiring ultrasound images include high acquisition speed, high rate of sampling, and faster processing unit, which are costly and power-consuming. However, the compressed sensing-based approach has shown significant advantages to ultrasound imaging [13]. In ultrasound imaging, images are acquired by the beamforming of the set of raw RF signals received transducer element. Compressed sensing reduces the number of the transducer elements, thereby reducing acquisition time and power consumption. Several Compressed sensing (CS) algorithms applicable to ultrasound have been investigated in various research studies to improve CS reconstruction techniques to achieve good quality images at reduced acquisition time and power consumption to improve cancer diagnosis. For example, CS-based deep learning was used in ultrasound imaging in liver classification [14] and the classification of breast lesions [15].

Despite the advantages of CS based techniques in ultrasound imaging, there is no perfect CS based algorithm in ultrasound. Each acquisition and reconstruction algorithm has its disadvantages, and there is always a trade off between reconstructed image quality, computational complexity and noise in the image [13].

Conclusion

Compressed sensing has been widely applied in various areas of biomedical imaging. It is been used to overcome most challenges including high ionizing radiation, increased data acquisition time, and high power computing inherent in most medical modalities such as Magnetic resonance imaging, computed tomography, X-rays, ultra sound and more. Aside from this, it offers an advantage of reconstructing images with enhanced quality, ensuring patient safety, and improving clinical decisions. Nevertheles, there are problems including low computation speed in MRI, and over smoothening of region of low contrast in CT scans involved in this method (compressed sensing) which needs to be handled. Further research should be carried out on ways to address these problems

QUESTION 2

Introduction

This section focuses on reconstructing images (random and hg) using orthogonal illumination and the compressed sensing approach by minimizing the total variance of the final image.

The illumination dataset and files used in the project work were acquired from Dr Michael. The illumination data were grouped into two data folders, namely “random” and “hg”, each containing positive and negative intensity profiles used for incoherent structured illumination. The CSV file dataset includes Illum-phantom-random, Illum-USAF-random, Illum-phantom-hg, and Illum-USAF-hg contained projection/illumination coefficients in reconstructing both random and hg images for phantom and USAF, respectively.

Six (6) Variables were created to store the Total illumination profile, positive intensity profiles and negative intensity profiles of both random and hg illumination dataset. The Total illumination profile was calculated by taking the difference of each positive and negative image intensity profile present in the random and hg dataset. Additionally, four (4) variables were created to store the projection coefficients found in the CSV Files.

The results realized in applying both orthogonal and compressed sensing approach to reconstruct the images are discussed and shown in the section below;

2a) Check that the illuminations are orthogonal and normalized.

Before reconstructing the images (random and hg) for both phantom and USAF, the image illuminations were checked to see if they were orthogonal and normalized. Orthogonality was checked to ensure that the image intensity profiles (625 positive and negative images, respectively) were completely independent on each other. Orthogonality was computed by taking the dot product of both positive and negative intensity profile[16]. The result of the computation evaluates to **0**, indicating that the illuminations (both random and hg) were orthogonal.

Furthermore, the illuminations for the images were checked to ensure they were normalized. To achieve this, the minimum and maximum intensity profiles for each illumination were calculated. The result of this evaluates to be between **0 and 1** for both minimum and maximum intensity profiles, respectively, indicating that the illuminations were normalized.

2b) Reconstruct the image taking into account the illumination profiles and the “*.csv” files using the orthogonal illumination approach.

Upon checking that the illuminations for both random and hg dataset were orthogonal and normalized, the total illumination profile was computed for the illuminations. This was done by taking the difference of each positive and negative part of the illumination profiles. Upon concluding, a total of 625 total illumination profiles was obtained. Finally, the image was constructed by multiplying each “total illumination profile” with its corresponding “illumination/projection coefficients” and then summing the results altogether. The result is as shown in fig(2a), 2(b), (2c) and (2d) for reconstructed random phantom, hg phantom, random USAF and hg USAF images, respectively

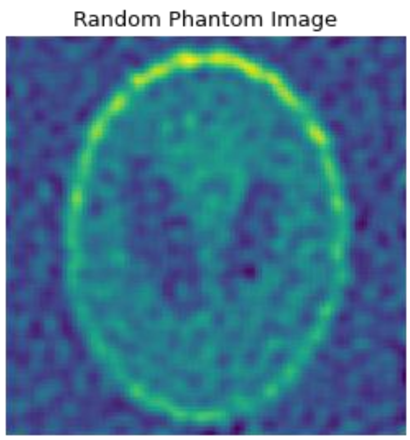

Fig 2(a): Reconstructed Random Phantom Image

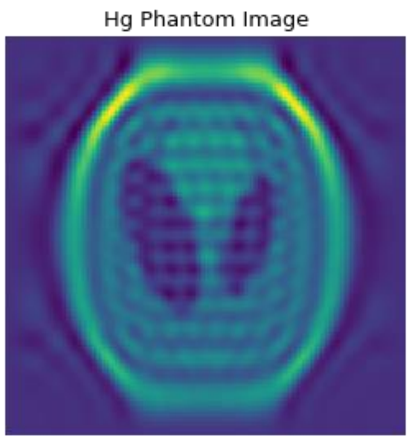

Fig 2(b): Reconstructed Hg Phantom Image

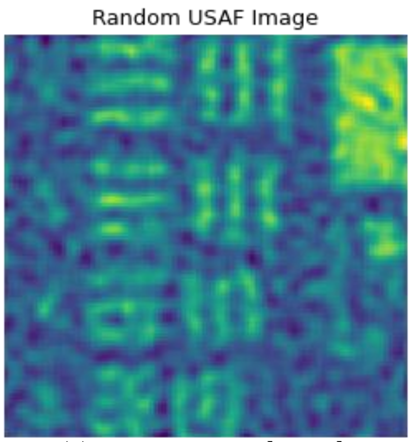

Fig 2(c): Reconstructed Random USAF Image

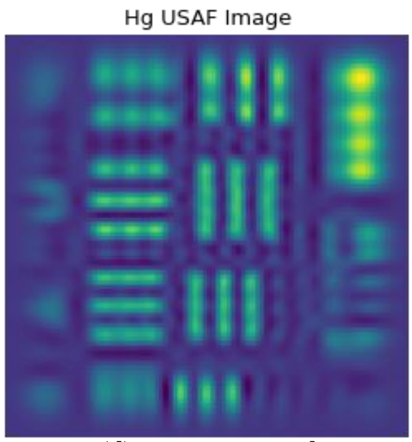

Fig 2(d): Reconstructed Hg USAF Image

Fig 2(a)(b)(c)(d): A figure showing the random-phantom, hg-phantom, random-USAF, and hg-USAF reconstructed images, respectively, using the orthogonal illumination approach.

2c) Reconstruct the image using the compressive sensing approach by minimizing the total variance of the final image.

In this part, the image was reconstructed using the compressive sensing approach. This was done by minimizing the total variance of the unknown (reconstructed image) subjected to some set constraints. The equation for this process is as represented below;

$$Min\ [tv(U)], subject\ to\ C_K = \sum b_{ij}^{(k)}\ U_{ij}$$

Where C_K represents the k-th illumination coefficient as contained in the CSV files, $b_{ij}^{(k)}$ represents the field for the k-th illumination (total illumination profile) at position ij and U_{ij} represents the pixel value in position ij of the unknown sample.

The unknown sample 'U' was created using a function cp.Variable (shape=160,160)) [17], where shape represents the shape of the unknown sample (160 rows by 160 columns). After which, an objective function was set to minimize the sample $Min\ [tv(U)]$. The process was done using total variation (tv).

A set of 625 equality constraints was set; where the constraints satisfied the equation $C_K = \sum b_{ij}^{(k)}\ U_{ij}$. Furthermore, an optimization problem was defined by subjecting the objective function to the set of constraints that were created. This process was done using the function cp.Problem() [17]**.** Finally, the problem was solved using SCS solver [18]**.** This generated a minimum value (optimal value) of the objective overall choices of variables that satisfy the constraints. After solving the problem, the reconstructed image was stored in U.value.

The result of this problem is as shown below in fig (2e), (2f), (2g), and (2h), for the reconstructed images.

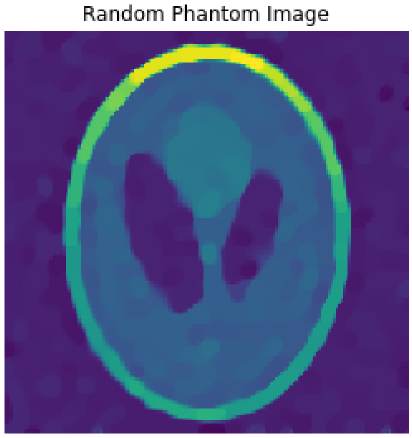

Fig 2(e): Reconstructed Random Phantom Image

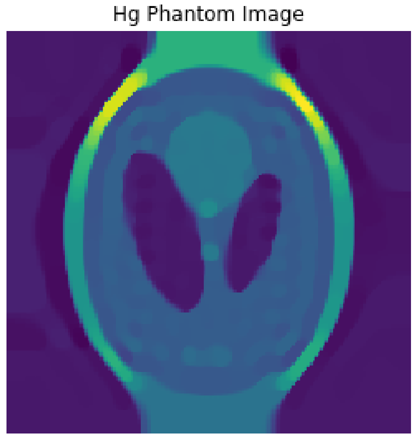

Fig 2(f): Reconstructed Hg Phantom Image

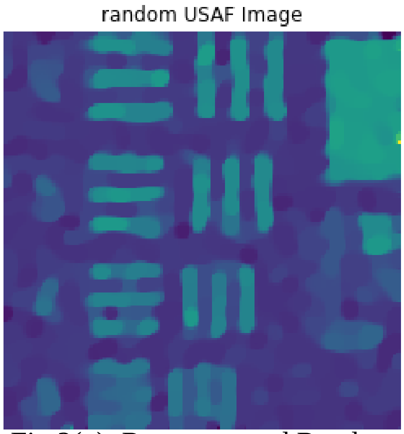

Fig 2(g): Reconstructed Random USAF Image

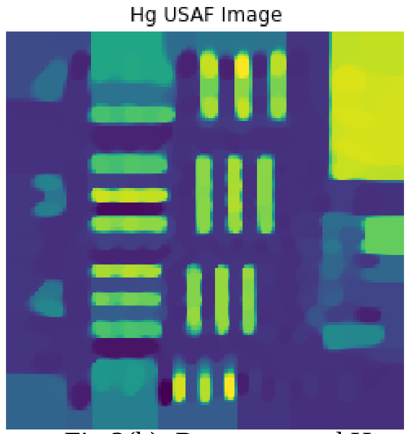

Fig 2(h): Reconstructed Hg USAF Image

Fig 2(e)(f)(g)(h): A figure showing the random-phantom, hg-phantom, random-USAF, and hg-USAF reconstructed images, respectively, using the compressive sensing approach.

2d) Compare and discuss the results from the two reconstruction methods using both illumination beams.

As seen in fig (2a),(2b),(2c), and 2(d), the reconstructed images using the orthogonal illumination approach had a low quality as compared to the reconstructed images (see fig(2e),(2f)(2g), and (2h)) produced using compressive sensing approach. Also, From the images generated for both random and hg images (for usaf and phantom), hg illumination generated images with a better spatial resolution. Thus, it can be concluded that using compressed sensing generated images with better spatial resolution than the orthogonal illumination.

REFERENCES

1. Graff, C.G. and E.Y. Sidky, *Compressive sensing in medical imaging.* Applied optics, 2015. **54**(8): p. C23-C44.
2. Brenner, D.J. and E.J. Hall, *Computed tomography—an increasing source of radiation exposure.* New England Journal of Medicine, 2007. **357**(22): p. 2277-2284.
3. Hartwig, V., et al., *Biological effects and safety in magnetic resonance imaging: a review.* International journal of environmental research and public health, 2009. **6**(6): p. 1778-1798.
4. Wang, G., Y. Bresler, and V. Ntziachristos, *Guest editorial compressive sensing for biomedical imaging.* IEEE transactions on medical imaging, 2011. **30**(5): p. 1013-1016.
5. Sandilya, M. and S. Nirmala, *Compressed sensing trends in magnetic resonance imaging.* Engineering science and technology, an international journal, 2017. **20**(4): p. 1342-1352.
6. Huang, J., L. Wang, and Y. Zhu, *Compressed sensing MRI reconstruction with multiple sparsity constraints on radial sampling.* Mathematical Problems in Engineering, 2019. **2019**.
7. Nan, Y., Z. Yi, and C. Bingxia. *Review of compressed sensing for biomedical imaging*. in *2015 7th International Conference on Information Technology in Medicine and Education (ITME)*. 2015. IEEE.
8. Zhu, Z., et al., *Improved compressed sensing-based algorithm for sparse-view CT image reconstruction.* Computational and mathematical methods in medicine, 2013. **2013**.
9. Sidky, E.Y. and X. Pan, *Image reconstruction in circular cone-beam computed tomography by constrained, total-variation minimization.* Physics in Medicine & Biology, 2008. **53**(17): p. 4777.
10. Sidky, E.Y. and X. Pan. *Accurate image reconstruction in circular cone-beam computed tomography by total variation minimization: a preliminary investigation*. in *2006 IEEE Nuclear Science Symposium Conference Record*. 2006. IEEE.
11. Tian, Z., et al., *Low-dose CT reconstruction via edge-preserving total variation regularization.* Physics in Medicine & Biology, 2011. **56**(18): p. 5949.
12. Cronan, J.J., *Ultrasound: is there a future in diagnostic imaging?* Journal of the American College of Radiology: JACR, 2006. **3**(9): p. 645-646.

13. Yousufi, M., et al., *Application of compressive sensing to ultrasound images: A review.* BioMed research international, 2019. **2019**.
14. Wu, K., X. Chen, and M. Ding, *Deep learning based classification of focal liver lesions with contrast-enhanced ultrasound.* Optik, 2014. **125**(15): p. 4057-4063.
15. Cheng, J.-Z., et al., *Computer-aided diagnosis with deep learning architecture: applications to breast lesions in US images and pulmonary nodules in CT scans.* Scientific reports, 2016. **6**(1): p. 1-13.
16. Wikipedia. *Orthogonality*. [cited 2021 17 May]; Orthogonality of Vectors]. Available from: https://en.wikipedia.org/wiki/Orthogonality#:~:text=In%20mathematics%2C%20orthogonality%20is%20the,contain%20nonzero%20self%2Dorthogonal%20vectors.
17. CVXPY. *Linear optimization with cvxpy*. 2021]; cvxpy]. Available from: https://cvxpy.readthedocs.io/en/latest/tutorial/intro/#:~:text=CVXPY%20is%20a%20Python%2Dembedded,solver%2C%20and%20unpacks%20the%20results.&text=The%20status%2C%20which%20was%20assigned,the%20problem%20was%20solved%20successfully.
18. Diamond, S. and S. Boyd, *CVXPY: A Python-embedded modeling language for convex optimization.* The Journal of Machine Learning Research, 2016. **17**(1): p. 2909-2913.