MR simulator to create tailored datasets of MR Images for AI Algorithm Development.

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I. INTRODUCTION

A. Background and Motivation

When it comes to detection of tumors and other medical anomalies, MRI is one of the most useful technologies available with us today. It uses magnetic properties of different tissues to create images where different types of tissues are distinguishable. In the recent years, as Machine learning and artificial intelligence continue to develop, their use in detection of tumors is a hot research topic. Using AI for detection eliminates chances of human error. One major problem is that training AI models requires large amounts of labelled data. We do not have large amounts of labelled MRI data available. Most hospitals do not have the systems and infrastructure to save and share labelled MRI data. Most of the data is lost. Patient privacy concerns further add to the difficulties in obtaining large amounts of data for training AI/ML models. Obtaining this data from MRI machines is a complex, labor-intensive and costly process. This has created a need for an MR simulator.

B. Literature Review and Present Work

One such simulator is MRiLab. The MRiLab is a numerical MRI simulation package. It has been designed and optimized to simulate MR signal formation, k-space acquisition and MR photo reconstruction. MRiLab offers numerous dedicated toolboxes to analyze RF pulse, layout MR sequence, configure transmitting and receiving coils, look at magnetic field related properties and evaluate real-time imaging approach. The primary MRiLab simulation platform blended with those toolboxes can be utilized out to customize diverse digital MR experiments which can serve as a previous stage for prototyping and trying out new MR method and software. The MRiLab capabilities include a tremendously interactive graphical user interface (GUI) for the benefit of speedy experiment design and technique prototyping. High simulation accuracy is obtained through simulating discrete spin evolution at small time interval the use of the Bloch-equation and appropriate tissue model. In order to manipulate multidimensional spin array, MRiLab employs parallel computing by incorporating state-of-the-art graphical processing unit (GPU) approach and multi-threading CPU technique. With efficient parallelization, MRiLab can accomplish multidimensional multiple spin species MR simulation at high simulation accuracy and time efficiency, and with low computing hardware cost.

II. DETAILED DESIGN OF SYSTEM

A. Basics of MRI

MRI uses the magnetic properties of tissues to create images. Different tissues with different magnetic proprieties generate signals of varying strengths which helps us differentiate tissues. The signals are generated in response to pulses. There are different types of sequences that can be run. One basic sequence is the spoiled gradient echo sequence. In the experiments we carried out this is the sequence we have used. In this sequence, any residual magnetization left after a pulse is removed before another pulse if given.

B. Some important MRI parameters

- TE: Time to Echo (TE) is the time taken to recieve the echo signal after delivery of the
- TR: Repetition Time (TR) is the amount of time between successive pulse sequences applied to the same slice
- FA: The flip angle is an MRI phenomenon by which the axis of the hydrogen proton shifts from its longitudinal plane (static magnetic field B0) Z axis to its transverse plane XY axis by excitation with the help of radiofrequency (RF) pulses

C. MRiLab: How it Works

Phantoms: Phantoms are mathematical models that represent physical objects/body parts. MRiLab also provides with a phantom designs panel where one can design phantoms . It come with some sample phantoms. The sample phantoms Brain High Resolution Phantom and Water Fat Phantom were used in the experiments we conducted. Sequences: MRIlab provides multiple sequences that can be run on a phantom. There is also a sequence design panel which can be used to design new swquences. Parameters: MRIlab allows us to tweak almost any parameters. We can control the nuber of slices, slice thickness, field of view,magnetic field, repetition time and many other parameters to get desired images. Output Images: MRIlab produces greyscale output images which are saved in a .mat file. The dimentions of the output image for the experiments we conducted were 80¿¡100.

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III. Experiments

Our experiments were confined to the Spoiled Gradient Echo Sequence for the Brain High Resolution Phantom and the Water Fat Phantom. For both the phantoms we did experiments varying various parameters. All the experiments were carried out for three noise levels 0, 5, 10. For Each Noise level the following experiments were carried out.

- Vary TE while keeping all other parameters constant (TE = 5 - 100 ms; steps: 10 ms (5,10,20,30,....) , TR = 500 ms, FA = 30°).
- Vary TR while keeping all other parameters constant (TR = 25 - 500 ms; steps: 25 ms) , TE = 5 ms, FA = 30°).
- Vary FA while keeping all other parameters constant (FA 5° - 90°, steps: 5°; TE = 5 ms, TR = 500ms).
- Vary FA while keeping all other parameters constant (FA 5° - 90°, steps: 5°; TE = 5 ms, TR = 40ms).

Results of the above experiments provided 80¿¡100 images. Certain pixels were selected to correspond to various tissues. In all the experiments the pixels chosen remained the same, so did the slices and the field of view. This was to ensure uniformity in the experiments.

Pixels Selected For signal and Noise computation from images obtained from the experiments

- For Noise: Four Patches(i= [4-8], j= [4-8]), (i= [72-76], j= [4-8]), (i= [4-8], j= [92-96]), (i= [72-76], j= [92-96]) (64 total Pixels)
- For CSF Signal: One patch (i= [38-42], j= [38-42]) (16 total pixels)
- For White Matter: One Patch (i= [38-42], j= [23-27]) (16 total pixels)

Results of the above experiments were loaded into python and mean values of signal for various tissues(CSF and White Matter) were computed. Expected signals were also computed using theoretical equation for computation of signal in a spoiled gradient echo sequence. Parameters that indicate magnetic proprieties(T1, T2 and T2*) for the tissues were obtained from MRiLab itself.

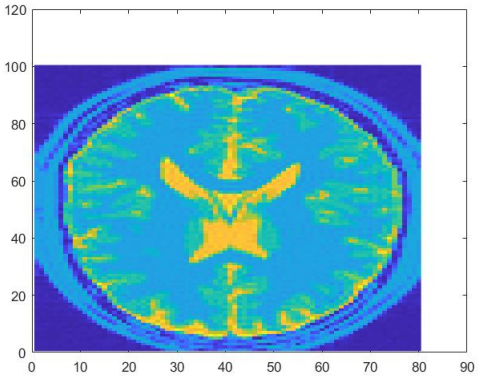

Fig. 1. A sample output image with dimensions

$$\text{Signal} = \rho \frac{\sin\alpha \cdot [1 - \exp(-\text{TR}/\text{T}_1)] \cdot \exp(-\text{TE}/\text{T}_2^*)}{1 - \cos\alpha \exp(-\text{TR}/\text{T}_1)}$$

Fig. 2. Equation for Noise Clacuation for Spoiled Gradient Echo Sequence

IV. Results and Discussion

The results of benchmarking the Spoiled Gradient Echo Sequence for MRiLab are mentioned below. During the benchmarking of the tool, we varied only four MRI parameters i.e. flip angle, repetition time (TR), echo time (TE) and hardware noise level. The results are helpful to understand whether the simulator is working correctly or not. By working correctly, we mean to check that the signal achieved from the phantom undergoing MR imaging (simulation) resembles the theoretical signal or not, and if the noise in the image resembles that of a real MR machine.

On Varying TE, at fixed FA = 30° and TR = 500 ms, the simulations worked well for TE values less than 20 ms. But for TE values greater than or equal to 20 ms, the MRiLab showed an error caused due to constants set internally. These constants were used to simply the computation process while solving the Bloch equations. However, this **inability to perform simulations for certain TE values** was not expected and is a limitation of MRiLab.

On Varying TR, at fixed FA = 30° and TE = 5 ms, the simulations follow very different patterns for different noise levels. And more importantly, none of these patterns resemble to that of the theoretical signal values. Fig 3 and Fig 4, shows how the theoretical signal varies with TR, and how the signal computed from image generated by MRiLab varies with TR for Cerebrospinal Fluid (in Fig 3) and White Matter (in Fig 4). We observe no resemblance of MRiLab signal patterns for different noise levels i.e. 0, 5, and 10 with the theoretical signal pattern for both CSF and WM. However, this **inability to resemble theoretical signal while varying TR values** was not expected and is another limitation of

MRiLab. Further, it is very strange that at Noise level = 0, we observe no change in Signal while varying TR values for both CSF and WM. Even this **inability of signal to vary with different TR values** is another limitation of MRiLab.

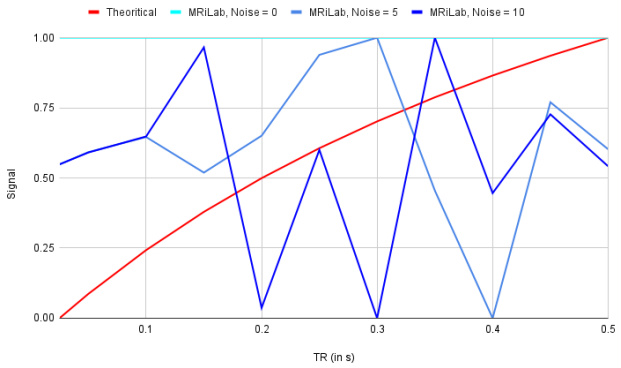

Fig. 3. Theoretical Vs Actual Normalised Signal on varying TR for CSF

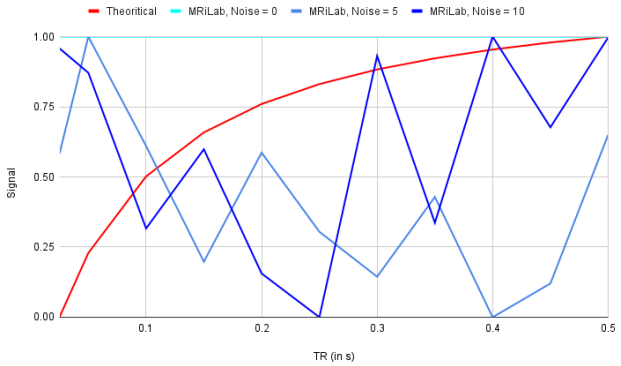

Fig. 4. Theoretical Vs Actual Normalised Signal on varying TR for WM

On varying flip angle, at fixed TE and TR values, the MRiLab simulations showed a monotonous increase in signal strength (brightness) with an increase in flip angle. Fig 5, shows three MR images of brain high-resolution phantom, where the parameter, flip angle was varied from 30° to 60° to 90° moving in the right direction. The noise level (hardware parameter, taken by MRiLab) was kept at 5, and all the images obtained are converted into grayscale by dividing by the maximum signal value of a phantom location (pixel in the image) for any of the above MR Image. It is to be noted that signal magnitudes for the entire image (brain high-resolution phantom) improves which indicates that whether it is cerebrospinal fluid (CSF), white matter (WM), fat, muscle or any constituent of brain phantom, its signal strength will increase on increasing the flip angle. A very similar increase in signal strength when the experiments were repeated at Noise level 0 and Noise level 10. The

On Varying flip angle for two different TR, we observe no difference in the signal obtained at any noise level. Fig 6 and Fig 7, shows how the theoretical signal varies with flip angle, and how the signal computed from image generated

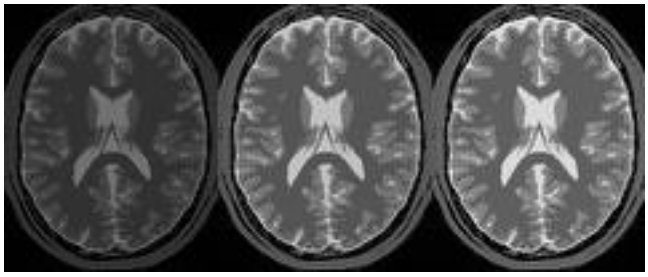

Fig. 5. MR images on increasing flip angle (left to right)

by MRiLab varies with flip angle for Cerebrospinal Fluid (in Fig 6) and White Matter (in Fig 7) at TR = 40 ms and TR = 500 ms. We observe no resemblance of MRiLab signal patterns with the theoretical signal pattern for both CSF and WM. However, this **inability to resemble theoretical signal while varying FA values** was not expected and is another limitation of MRiLab. Further, it is very strange that at two different TR values, we observe absolutely similar signal while varying flip angle values for both CSF and WM, at any noise level. Even this **inability of signal to vary with flip angle for different TR values** is another limitation of MRiLab.

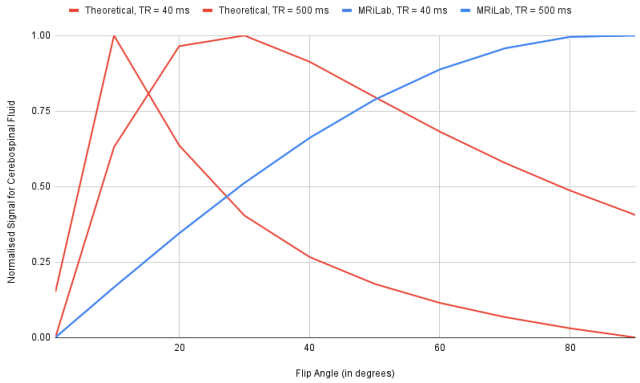

Fig. 6. Theoretical Vs Actual Normalised Signal on varying flip angle for CSF

Theoretically, on increasing flip angle we observe an increase in signal, after some time the signal decreases with increasing flip angle. The point of maxima occurs, when the flip angle is equal to the Ernst angle. This is a basic concept in MR imaging, which is violated in the MRiLab simulations, as seen in Fig 5 and Fig 6. We can clearly see the monotonous increase in signal on increasing flip angle in Fig 3. However, this **inability to consider the basic MRI concept maximum signal at Ernst angle while varying flip angle** was not expected and is another limitation of MRiLab.

We also looked into the noise computation model of MRiLab, where we understood that the simulator adds Gaussian noise with zero mean and user-defined standard deviation (referred to as Noise Level) to acquired k-space data. Fig 7, shows the formula used for calculation of noise by MRiLab. It would have been interesting to check the correctness

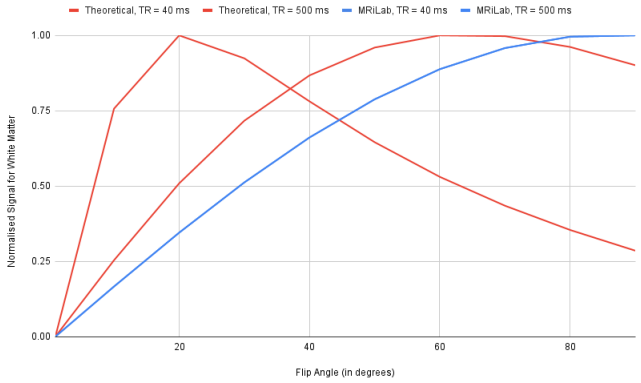

Fig. 7. Theoretical Vs Actual Normalised Signal on varying flip angle for WM

of the added noise, by comparing it to real MR images. However, there are **multiple flaws in calculation of Signal, which inhibits our progress in benchmarking the noise computation model of MRiLab.**

$$Noise = \frac{\frac{NoiseLevel}{NoiseRef} \times \sqrt{\frac{BandWidth}{BWRef}}}{\frac{B0}{B0Ref} \times \frac{RFreq \times RPhase \times RSlice}{VolRef} \times \sqrt{\frac{NEX}{NEXRef}} \times \frac{ResFreq \times ResPhase \times SliceNum}{ADCRef}}$$

Fig. 8. Equation for calculating noise

Future Plan

The Experiments performed so far show that MRiLab does not calculate the signal as it should. The Software does not seem to work for some given values of parameters and gives an error.

In the next semester, we will try to create a noise computation model that produces more realistic noise. We will also try to update and replace the equation for signal calculation for the spoiled gradient echo sequence. Thereafter, we will try to add functionality to add tumors to the phantoms to create tailored labelled data sets. Please refer to the last page for Gantt Chart.

Conclusion

The MRiLab despite being a user-friendly software did not meet the expectations during our benchmarking progress. We see that the signal does not vary as it should. The results from the experiments show that the noise computation model is not accurate. The benchmarking process for the noise computation model would be difficult, considering the multiple flaws in the signal computation. This software tool can be of great use in creating tailored data sets. If the problems with it are fixed, it can provide enough data to train AI based algorithms for tumor detection. Adding the functionality to add tumors will also be a good addition and can increase the scope of applications of this useful software tool.

References

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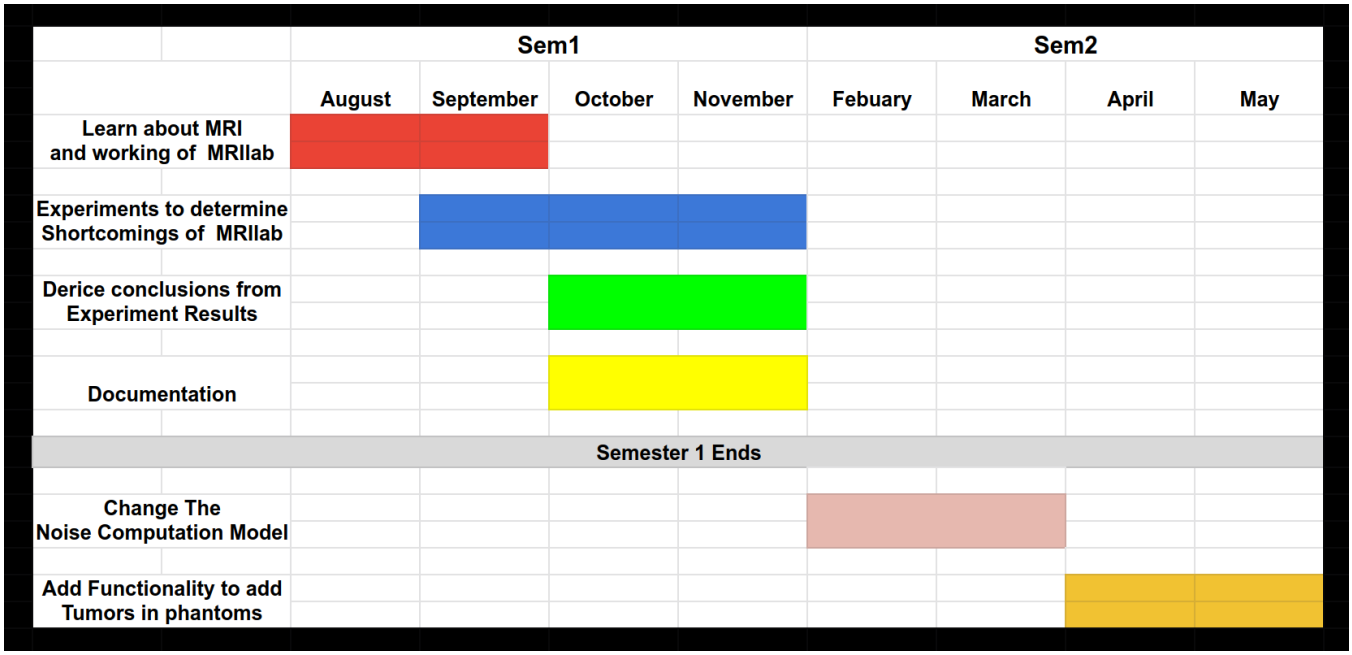

Fig. 9. Gantt Chart