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Research Article

Development of Machine Learning Based Algorithm for Computational Multidimensional Correlation Magnetic Resonance Imaging

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Abstract
The possibility of non-invasively performing quantitative measurements of the physical properties of living tissue such as the diffusion coefficient and the relaxation times T_1 and T_2 during magnetic resonance imaging (MRI) require length acquisition time. To guarantee a sufficient signal-to-noise ratio (SNR) the image resolution is often sacrificed. The available method presently in use requires repeated acquisitions and averaging them, which is time-consuming. This model offers a computational method with the aid of a machine learning approach. The python approach obtained the result in 3 seconds for T_1 and 2 seconds for T_2 respectively.
Keywords: Diffusion coefficient, Relaxation time, Magnetic, Resonance imaging

Introduction

The early history of medical diagnosis associated with nuclear magnetic resonance (NMR) traditionally with spectroscopy, as chemical shift resolution enabled chemists and structural biologists to deduce the structures of increasingly complex molecules. Since the 1980s, the medical community has been exploiting the spatial resolution afforded by magnetic resonance imaging (MRI) for diagnosis and therapy [1].
Magnetic resonance imaging (MRI) is a medical imaging technique used in radiology to form pictures of the anatomy and the physiological processes of the body. The original name for MRI was called NMRI (nuclear magnetic resonance imaging), but "nuclear" was dropped to avoid negative associations [2]. Certain atomic nuclei can absorb and emit radiofrequency energy when placed in an external magnetic field. Hydrogen atoms are most often used to generate a detectable radio-frequency signal that is received by antennas close to the subject being examined. Since hydrogen atoms are naturally abundant in humans and other biological organisms, MRI takes advantage of this, particularly in water and fat. For this reason, most MRI scans essentially map the location of water and fat in the body. Pulses of radio waves excite the nuclear spin energy transition, and magnetic field gradients localize the signal in space. The excited atoms emit a radio frequency (RF) signal, which is measured by a receiving coil. The RF signal may be processed to deduce position information by looking at the changes in RF level and phase caused by varying the local

magnetic field using gradient coils. As these coils are rapidly switched during the excitation and response to perform a moving line scan, they create the characteristic repetitive noise of an MRI scan as the windings move slightly due to magnetostriction. The contrast between different tissues is determined by the rate at which excited atoms return to the equilibrium state. Exogenous contrast agents may be given to the person to make the image clearer[2]. By varying the parameters of the pulse sequence, different contrasts may be generated between tissues based on the relaxation properties of the hydrogen atoms therein.

In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools to solve complex problems associated with a medical diagnosis. However, whereas traditional (ML) algorithms used pre-engineered features to develop predictions; the deep learning (DL) technique processes medical imaging data for several tasks like image classification, segmentation, registration, and abnormality detection. DL algorithms can learn the optimal features that best fit the data through the training process, avoiding the need to use pre-engineering, unstructured data [3].

Magnetic Resonance Imaging (MRI) is a fundamental asset for clinical assessment and diagnosis in modern healthcare. The pathway to its success is the possibility of non-invasively performing quantitative measurements of the physical properties of the living tissue such as the diffusion coefficient and the relaxation times T_1 and T_2. However, this requires lengthy acquisitions to collect high-resolution images at different contrast [4]. Thus, to guarantee a sufficient signal-to-noise ratio (SNR) the image resolution is often sacrificed. The available way of obtaining high resolution and SNR presently in use requires repeated acquisitions and averaging them [5], which is time-consuming.

Combining multidimensional NMR-based spectral methods with spatial localization via MRI is required to be able to assess the heterogeneous properties of such tissue. For more than two decades, this challenge has seemed insurmountable, owing to the vast amount of data required and other computational challenges [5]. Integration of this multidimensional approach within imaging applications was not feasible until recently due to burdensome data requirements causing impractical scan times. The development of the marginal distributions constrained optimization (MADCO) framework had minimized data requirements, leading to the feasibility of multidimensional correlation imaging[6].

The most commonly used method for dimensionality reduction in this context is finding spectral regions of interest (ROIs) that contain peaks, and summing (i.e., numerically integrating) over them [5].

The challenge associated with spectra is that of defining the ROIs whose spectral peaks in many instances overlap or are somewhat indistinguishable [7]. Moreover, with an imaging volume that easily contains thousands of voxels, an automated and robust method to correctly identify the ROI is needed [5]. It is to this end that the present study posits to develop machine learning based algorithm for computational multidimensional correlation magnetic resonance imaging.

Computational method

The general equation which governed NMR is the Bloch NMR flow equations; it relates macroscopic concept of magnetization to the applied radiofrequency, gradient and static magnetic fields [8].The Bloch NMR equations of coupled differential equations describing the behaviour of the macroscopic magnetization vector under any conditions is given by:

$$\begin{aligned} \frac{dMx}{dt} &= \frac{\partial Mx}{\partial t} + v\frac{\partial Mx}{\partial x} = -\frac{Mx}{T1} \\ \frac{dMx}{dt} &= \frac{\partial My}{\partial t} + v\frac{\partial My}{\partial x} = \gamma M_z B_1(x) = \frac{M_y}{T_2} \\ \frac{dMx}{dt} &= \frac{\partial Mz}{\partial t} + v\frac{\partial Mz}{\partial x} = -\gamma M_z B_1(x) = \frac{M_o - M_z}{T_1} \end{aligned} \quad (1)$$

The set of analytical solution of the system of equation with initial conditions is given as:

$$M_x(t) = e^{-t/T_2(M_x(0)Cos\omega_o t + M_y(0)Sin\omega_o t)}$$
$$M_y(t) = e^{-t/T_2(M_y(0)Cos\omega_o t - M_x(0)Sin\omega_o t)} \quad (2)$$
$$M_z(t) = M_z(o)e^{-t/T_1} + M_o(1 - e^{-t/T_1})$$

The Time-Dependent Bloch NMR Flow equationT_1 Calculation

Theory

The solution to this more complete representation of the Bloch equations yields the following time dependence for the longitudinal component of the magnetization:

$$M_z(t) = M_z(o)e^{-t/T_1} + M_o(1 - e^{-t/T_1}) \quad (3)$$

where the term M_o is the equilibrium magnetization and the term $M_z(o)$represents any remnant longitudinal magnetization that still presents at time *t* = 0 from any previous manipulations of the spin system. When $M_z(o)$ is zero, the expression simplifies to:

$$M_z(t) = M_o(1 - e^{-t/T_1}) \quad (4)$$

The longitudinal relaxation time (also known as the spin lattice relaxation time) T_1represents how quickly the spins become parallel to the magnetic field. Recall that there are many spins even in a small volume and so T_1 is considered with respect to a large number of spins, but in a volume small enough to be considered much less than the spatial scales of interest (such as the voxel dimension) [9]. This small volume is referred to as an isochromat of spins. Over a very long period of time relative to T_1, the magnetization will grow to nearly its maximum value, and $M_z(t)$ will become M_o. In practice, T_1 is considered to be the time it takes the signal to grow to 1 $-e^{-1}$ of its maximum value (~63%). From Equation 2 for instance, the signal is at 95% of its equilibrium value at $3T_1$, the signal is at 95%, which implies that, its value increases only slowly. This behavior as shown is an important aspect of tissue contrast in imaging sequences where multiple RF pulses are applied to completely cover *k*-space and the longitudinal magnetization has a limited time to re-grow [10]. For now, it is clear that, if there is a 90° RF pulse applied every T_R, then the longitudinal magnetization prior to each RF pulse will be as in equation 3 with *t* replaced by T_R.

$$M_z(T_R) = M_o(1 - e^{-T_R/T_1}) \quad (5)$$

T_2 Calculation

Theory

As seen above, T_2 solution can be obtained in a similar fashion. In order to detect any signal, some transverse magnetization needs to be created, conventionally; this is done by tipping the longitudinal magnetization into the transverse plane. Assuming no in homogeneities existed, and then transverse magnetization immediately after an RF pulse is donated by$M_{xy}(0)$, then:

$$M_{xy}(t) = M_{xy}(o)e^{-t/T_2} \quad (6)$$

However, transverse magnetization starts vanishing quickly once it exists. The reason has been that, local microscopic field inhomogeneities cause the spins to become irreversibly out of phase with each other, leading to signal loss. Because images are usually measured about a certain time, *T*E, after the RF pulse, the signal is given by:

$$M_{xy}(T_E) = M_{xy}(o)e^{-T_E/T_2} \quad (7)$$

The characteristic time T_2 is thus seen to be the time it takes for the signal to drop to 1/*e* of its original value (37% of its original value).s

Consequently, the rate at which the net longitudinal magnetization vector builds up again to the equilibrium values is constant and is expressed by the T_1 relaxation time. The rate at which the transverse magnetization vector decreases is also constant and expressed by the T_2 relaxation time. T_1 and T_2 are the major parameters influencing the amplitude of the magnetic resonance signal. They depend on the molecular environment of the tissue and allow the distinction of different types of tissues.

Results and Discussion

This work demonstrates the performance of Python's Machine learning based algorithm at different signal-to-noise ratios and the different T_1-T_2 spectral characteristics of multidimensional magnetic resonance. A graphical user interface that allows assembly of nodes for data analytical workflow, data integration, and pre-processing (Extraction, Transformation, Loading ETL) for modelling and data analysis and visualization is incorporated [11].

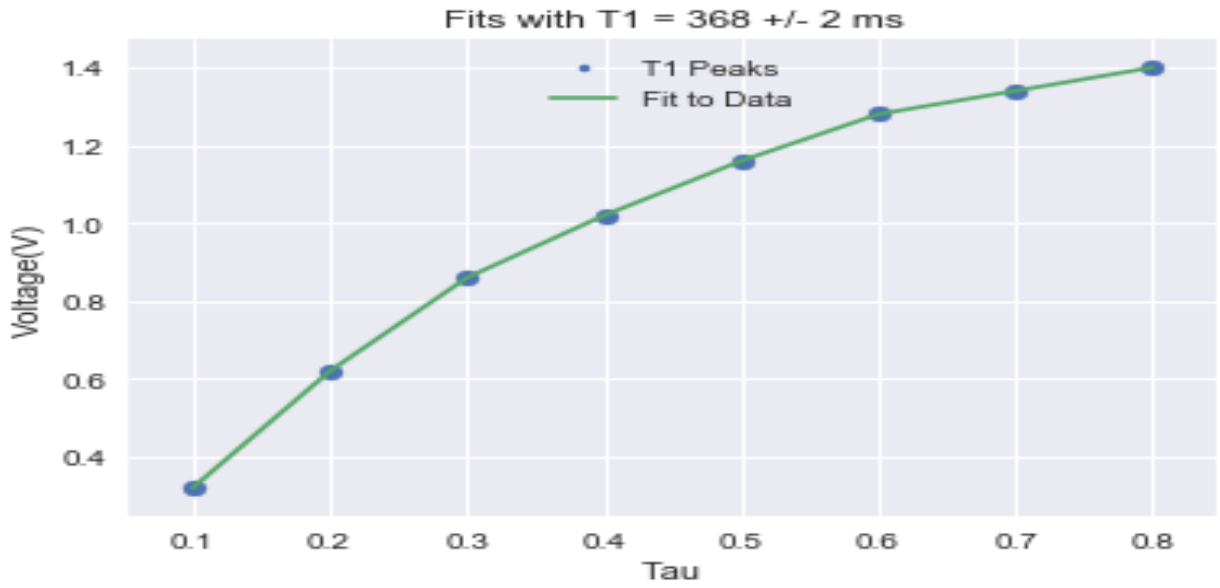

Figure 1. ***Python plots for T_1***

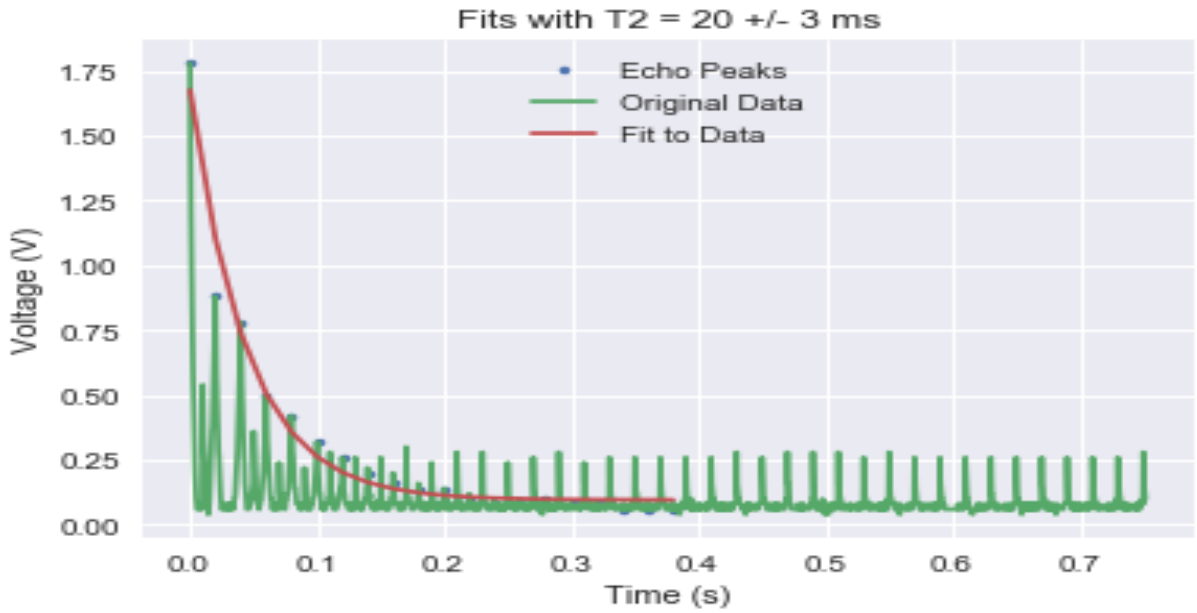

Figure 2. *Python Plots for T_2*

As demonstrated in the above plots, T_1 images are produced by short TE and TR and their brightness and contrast can be determined by T_1 properties of the chosen tissues while the second plots shows that, T_2-weighted images are produced by longer TE and TR and there contrast and brightness are predominately determined by the T_2 properties of the tissue.

Conclusion

The development of machine learning based algorithm for computational multidimensional correlation magnetic resonance imaging is presented. In this study, estimate model for relaxation parameters with good accuracy and precision similar to conventional Bloch MRI equation was developed. Machine learning algorithm approach as presented in this work and other similar work provide a promising application for multidimensional correlation with short time sequence.

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