Fast Calculation of T_2 Relaxation Time in Magnetic Resonance Imaging

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Abstract— The main parameters displayed by means of magnetic resonance include, for example, relaxation times T_1 and T_2 or diffusion parameters. This paper presents the computation of relaxation time T_2 measured indirectly with the Spin Echo method. The sensing coil of the tomograph provides a signal in which the important factor is the location of the peaks from individual measurements. These points must be interleaved with an exponential function. The relaxation time T_2 can be directly determined from the exponential shape. The described process has to be repeated for each pixel of the sensed tissue, and this requirement makes the processing of larger images very demanding in terms of both the actual computation and the time needed for the entire operation. More concretely, if we assume the common resolution of 256×256, 20 slices, and five measurements with different times T_E, it is necessary to reconstruct $1.3 \cdot 106$ exponential functions in total, which requires the processing of more than 6 MB of data. At present, such computation lasts approximately 3 minutes if performed by means of a regular PC. The author discusses various approaches to the parallelization of the given problem. In the described context, the time required for the processing of the applied three-dimensional image was shortened to 300 ms thanks to simple interpolation approach. The final section of the paper comprises a detailed comparison of the computation times characterizing both the sequential and the parallel solutions.

1. INTRODUCTION

The imaging of biological tissues carried out via magnetic resonance (MR) currently constitutes one of the most advanced diagnostic techniques [1, 2]. A large number of imaging sequences are available, and each of them finds its application in the imaging of a particular set of tissue properties [3, 4]. The most common tomographically acquired parameters include relaxation times T_1 and T_2. In this context, it is possible to point out that the higher the number of known tissue parameters, the better their discernibility (or the concrete pathology diagnosis) [5]. The relaxation time T_2, whose reconstruction is discussed within this paper, can be acquired via a number of sequences, and one of the techniques most widely used for the purpose is the Spin Echo (SE) method. In magnetic resonance, a spin echo is a pulse sequence comprising two radio frequency pulses with the phases of 90° and 180°. After the first pulse, the magnetization vector is flipped into the xy plane, and the T_2^* relaxation begins; this means that while some protons precess with slightly higher frequencies, others perform the same with lower ones. Subsequently, dephasing occurs. However, if there follows a 180° refocusing pulse, which will flip the individual spins in the xy plane, then the spins are in phase again, and the receiver coil detects a signal. The amplitude of the signal depends on the T_2 of the tissue. This process is repeated with the increasing time T_E, where $T_E/2$ is the time between the above-mentioned pulses with the phases of 90° and 180°. The time progression of the SE sequence is displayed in Figure 1.

The relaxation time T_2 is determined from the exponential function, which passes through the maximum values of the individual echoes. This function can be expressed as

$$E = e^{-\frac{T_E}{T_2}}, \tag{1}$$

where E is the envelope of the spin echoes, and T_E is the time of the echo arrival from the first excitation pulse. This time is given by double the time between the arrivals through the first and the second excitation pulses [6].

The determination of the relaxation time T_2 therefore comprises the following steps: acquisition of several images via the SE sequence with different times T_E; exponential regression at points located in the maxima of the individual echo signals; computation of the T_2 relaxation. The

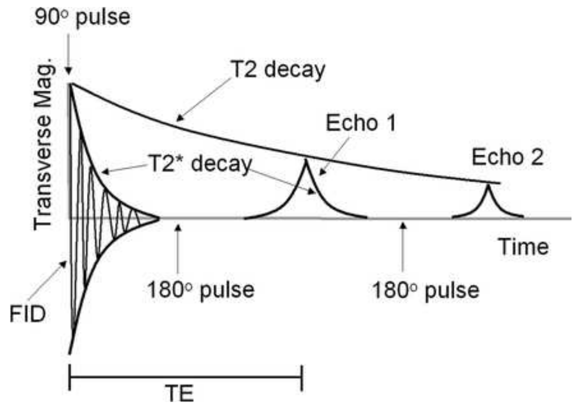


Figure 1: The time progression of the Spin Echo sequence and the T_2 exponential decay.

process is repeated for all pixels in the image. In the applied image having the size of 256×256 pixels and depth of 20 slices, this corresponds to $1.3 \cdot 106$ exponential regressions, and there are 5 points from which the exponential is reconstructed. It follows from the above-indicated facts that the computational problem is very extensive with respect to the data size. Generally, two solution options are available to eliminate the drawback. In the first approach, the problem is solved sequentially, and we have to perform (within each step) exponential regression from the five measurements for each voxel individually; the second option is based on the parallelization of the problem. The computation of the value of the relaxation time T_2 of each voxel depends only on the values obtained from the five measurements carried out with the SE technique, and therefore the regression can be performed for all voxels simultaneously.

The investigation of methods for the reconstruction of T_2 images has been described and discussed in a large number of papers, for example [7, 8]. Importantly, the most prominent disadvantage of the techniques can be identified in the computational speed, as suggested above. Recently, however, the drawback has been markedly suppressed by the application of high-speed graphic processors, which enable us to realize the computational process in a parallel — and very fast — manner [9, 10].

2. IMAGE DATABASE, HARDWARE & SOFTWARE

In order to test the proposed parallel processing method, we used a three-dimensional image of a brown rat; this image had been acquired via a Bruker Biospec 94/30 tomograph having the elementary magnetic field intensity of 9.4 T. The images exhibited the resolution of 256×256 pixels, and 20 slices were applied. Each voxel was measured five times using the SE method. The echo times T_E were selected as follows: 15 ms, 45 ms, 75 ms, 105 ms, 135 ms.

The actual comparison of the sequential and parallel variants of the computation of T_2 maps was performed with a PC comprising an Intel Core2 Quad 2.66 GHz, 4 GB RAM processor. The applied software included Windows 7 64-bit and Matlab R2013a. The parallel computing was carried out utilizing the CUDA platform containing the following graphics card: nVidia GeForce GTX 770 (1024 threads per block, max thread block size $1024 \times 1024 \times 64$, 4 GB of total memory at the frequency of 7 GHz, 1 GHz GPU).

3. METHODS

The aim of the processing is to obtain a T_2 map of the relaxation times of the tissues imaged during the tomographic measurement. In this respect, the paper describes two processing methods, namely a) sequential computation, and b) parallelized computation.

3.1. The Sequential Approach

The described reconstruction of the T_2 map from an MR set of images was implemented in the Matlab environment. Here, the computation proceeds in a single for cycle. Within each step of the program, the exponential regression of one pixel is performed from 5 measured values of the maximum intensity of the echo. The number of cycles is 1 310 720. The exponential regression initially employed the function fit, whose syntax is as follows:

$$\text{fitobject} = \text{fit}\ (x,\ y,\ \text{'exp1'});$$

where x is the vector of the times of the arrival of the echoes T_E, and y is the vector of the measured values of the maximum intensity of the echoes.

At the following stage, we implemented the method described and used in the parallel computation.

3.2. The Parallel Approach

The implementation of this option was also performed in the Matlab environment. In this approach, the computation is carried out in a single step, namely by calling the computational core of the graphics card. The computation of the value of each pixel is assigned one thread of the process.

In this experiment, the actual regression computation was performed using the conversion of exponential regression to linear regression. The measured values are assumed to approximately correspond to the functional dependence in the form

$$y = a \cdot e^{bx}. \tag{2}$$

If this formula is logarithmized, we obtain the linear equation

$$\ln y = \ln 1 + \ln e^{bx}. \tag{3}$$

After applying the method of least squares, we obtain the following relation for the calculation of the coefficient b:

$$b = \left[n \cdot \sum_{i=1}^{n} x_i \cdot \ln y_i - \sum_{i=1}^{n} x_i \cdot \sum_{i=1}^{n} \ln y_i \right] \Bigg/ \left[n \cdot \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i \right)^2 \right], \tag{4}$$

where the vector x represents individual times to the echoes T_E, the vector y denotes the measured values of the echoes, and n is the number of measurements. By comparing formulas (1) and (2) and through substituting the coefficient b from Equation (4), we obtain the relaxation time T_2 in the form

$$T_2 = -\frac{1}{b}. \tag{5}$$

The parallel computation always runs with only one slice of the 3-D image, whose resolution is 256×256 pixels (this value corresponds to 65536 threads of the graphics processor). The computation of the three-dimensional T_2 map is then carried out in a series-parallel manner.

4. RESULTS AND DISCUSSION

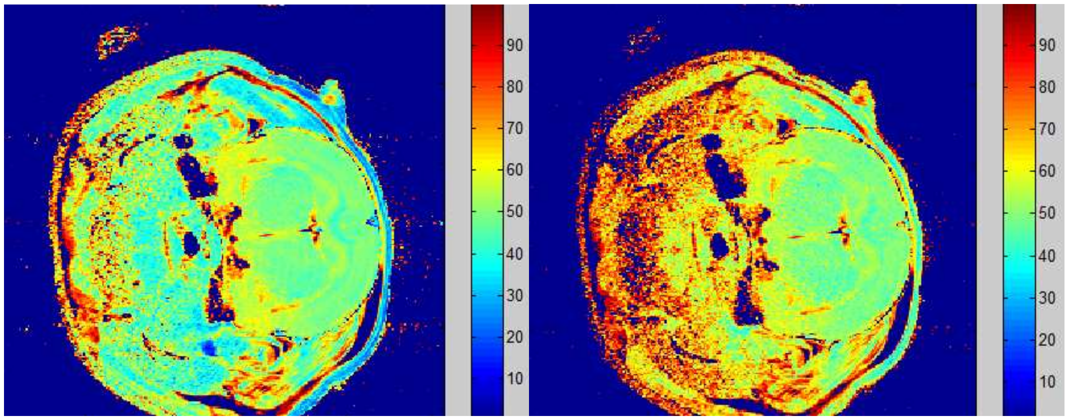
The comparison of the approaches to the computation of T_2 is realized with respect to both the time required by the process and the accuracy of the obtained values. In view of the large difference between the sequential and the parallel execution of the program, the comparison of the time requirements is carried out using a three-dimensional image, which exhibits the resolution of 256×256 pixels and where the total number of slices is 20. The comparison targeting the accuracy of the obtained values is materialized via subjective revision of the computed images and by means of the computation and analysis of the differential image.

For quick reference, the time requirement values are quoted in Table 1.

Table 1: Sequential and parallel computation: Values of the time required.

Computation	Time required per 1 slice	Time required per 20 slices
Sequential (the *fit* function)	41 min	$\approx$ 14 h
Sequential (function according to formula (8))	10.3 s	$\approx$ 210 s
Parallel	8.8 ms	167 ms

The correctness of the computation is verified by means of a difference image and its analysis. Figure 2 shows (a) the selected T_2 map in the 9th slice of the volume from the sequential computation using the fit function, and (b) displays the result of the parallel computation. Figure 3 presents the difference image which appears after the sequentially computed image is subtracted from the image obtained via the parallel computation.



(a) (b)

Figure 2: The resulting T_2-map obtained from the sequential and parallel computation. (a) Sequential computation result. (b) Parallel computation result.

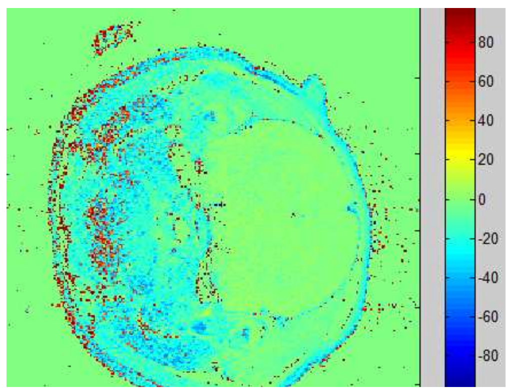


Figure 3: The image resulting from the difference between the results of the sequential and the parallel computation.

A subjective comparison of the images from Figures 2(a) and 2(b) will show agreement between the two methods of T_2 computation. Further, an analysis of the map obtained via parallel processing will indicate a higher sensitivity to noise, which is a factor that affects SE-based images already at the time of their making. This effect manifests itself mainly in the left portion of the image; such distribution of the problem is caused by a weak response of the examined tissues stemming from the fact that the image was produced using a surfaced coil located on the right-hand side. Principally, however, the above-described disadvantage cannot be ascribed to parallel image processing, and its origins should be sought in the applied exponential regression method.

The correctness of the result can be demonstrated also on the difference image displayed in Figure 3. Here, too, a higher error rate appears in regions exhibiting a lower level of the SE signal. The image background was subtracted before the actual computation of the T_2 map, and therefore the computational error is zero. Before subtraction of the background, the error rate in these regions is at its highest level, and the map can be displayed only with difficulty. In its left section, the differential image again exhibits a higher error rate caused by the location of the surface coil.

5. CONCLUSION

The article presents a solution enabling fast computation of images of the relaxation time T_2; such images are very often analyzed in the diagnostics and description of tissues performed within magnetic resonance tomography. In the given context, two computational methods are described. The first of these techniques consists in the standard sequential approach, where the value T_2 of the relaxation time is (in each pixel) computed within one step of the cycle of the common process thread. This technique requires a significant amount of time to perform a complete reconstruction (the process lasts 14 hours if the embedded m-function fit is applied, but it takes up less than 4 minutes with a simple regression function). Conversely, the parallel approach employing the

CUDA platform and utilizing effective computation performed by means of an nVidia graphics card requires approximately 200 ms to reconstruct a three-dimensional T_2 map having the size of $256 \times 256 \times 20$ pixels. The specified time can be even lower, and its concrete values then differ according to the graphics card used (the number of physically allocated CUDA cores), speed of the graphics processor, and memory. As shown in Figures 2, and 3, the images provided by both methods exhibited an identical structure of the displayed tissues. The results differ in the sensitivity to noise, mainly in regions with a low level of the SE signal. Such low level is caused by the location of the sensing surface coil of the tomograph. In the computation of T_2 relaxation times, the sensitivity to noise is a critical factor, and therefore the noise in the images has to be eliminated. This paper comprises a description of the exponential regression method converted to a linear problem. For future applications, the analysis of exponential regression results via other methods is assumed; one of related possibilities consists in the pre-processing of SE images to facilitate the suppression of noise or motion artefacts already in source images. The problems thus specified would then affect the resulting T_2 map only minimally.

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