Tissue characterization of potato tubers using localized MRI T2 Relaxometry

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Quantitative Magnetic Resonance Imaging (MRI) is an appropriate non-destructive tool to study plants and food internal structure and composition [1]. Among the various acquisition protocols available with MRI, T_2 relaxometry aims to measure the transverse relaxation times using a multi-echo spin echo (MSE) sequence which provides a set of images at a fixed sample rate along an exponential decay signal.

In the case of plants, the measured relaxation signal in each voxel can be modelled by a multi-exponential decay which corresponds to the sum of the signals of the different water pools. These water pools have generally been assumed to reflect subcellular compartmentation (vacuole, cytoplasm, cell wall) and/or heterogeneity of the tissue. MRI can therefore be used to access information about water status and distribution at the subcellular and tissue levels, which is very important for quality monitoring during storage, drying and transformation of plants.

Due to low signal to noise ratio, the estimation of these T_2 values is an ill-posed problem. An algorithm has been developed for their estimation, that includes a spatial regularization to obtain information at the voxel level [2], this can be seen as "localised T_2 relaxometry". Moreover, an unsupervised clustering approach has been proposed, allowing to exploit the T_2 values and amplitudes to distinguish biologically different tissues [3].

A recent study investigated internal defects in potato tubers and their evolution during storage with MRI [4]. After harvest, the tubers were stored at 5°C and MRI measurements were carried out 8 times from 14 to 33 weeks after harvest (WAH). Images of potato tubers were acquired on a 1.5 T MRI scanner with a resolution of 0.9 mm × 0.9 mm × 5.0 mm using a 2D MSE sequence with 256 echoes (t=7.4 to 1894.4 ms). The multi-T_2 evaluation was led at the scale of manually delimited region of interests (ROIs), whose signal was fitted according to the Levenberg–Marquardt algorithm.

The purpose of the work presented here was to apply the method presented in [3] to evaluate the feasibility of defects detection thanks to localised T_2 relaxometry. As potato tubers are complex organs made up of several tissues, an additional aim was to extend the study to the global characterisation of tuber zones. Four tubers with large defects detected in their perimedullary regions were selected.

The signal $s(x,t)$ in voxel x at echo time t was modelled as the sum of exponential decays of C components:

$$s(x,t) = \sum_{c=1}^{C} A_{0cx} e^{-t/T_{2cx}}$$

with A_{0cx}, the amplitude and T_{2cx} , the relaxation time, of component c in voxel x. The analysis of the Bayesian information criterion at 14 WAH, showed that C=2 was the optimal choice. This result is in concordance with a previous study using magnetic resonance relaxation where analysis of the relaxation decays revealed two major water populations in the potato [5]. This number of 2 components was retained for all the study. Thus, in each voxel, two relaxation times T_{21x} and T_{22x}, and the ratio of the shortest component $R_{01x} = \frac{A_{01x}}{A_{01x}+A_{02x}}$ were estimated.

Clustering was made using K-means algorithm with normalized T_{21x}, T_{22x} R_{01x}. The number of classes was manually set to 6. For each class, the distribution of the T_2 values was computed. The statistical difference between each class was performed using a Kruskal-Wallis test. Bonferonni correction was used as the control for multiple comparisons between each pair of classes.

Figure 1 shows (a) the 1st echo of the MRI images with the ROIs delimitating the defects as presented in [4], the estimated T_{21}, T_{22} and R_{01} maps, the classification map and the associated T_2 distribution for 14 WAH, (b) the classification map for 23 and 31 WAH. At 14 WAH, the 6 classes corresponded to the cortex, the pith, the defects, (resp. in dark purple, yellow and white) while the flesh tissue was divided in three classes (light orange, dark orange and light purple). The defects manually segmented were in good concordance with the classes with the highest T_{22} values. For some measurement days, they represented a single class, which allowed their automatic detection, for others they were classified together with the pith, due to similar T_{22} values. For each measurement day, the 6 classes were statistically different and their spatial arrangement was similar over time. Thus, localised T_2 relaxometry enabled to distinguish different tissues within the tubers and showed the heterogeneity of the flesh. This confirms observations with MRI for the study of potatoes sensory texture [6]. Moreover, the evolution of the T_2 distribution over time showed that the T_2 values of the 6 classes tended to converge, which could testify to the evolution of the cells during storage. All these observations tend to show that localised T_2 relaxometry is a valuable tool for plants tissue characterisation.

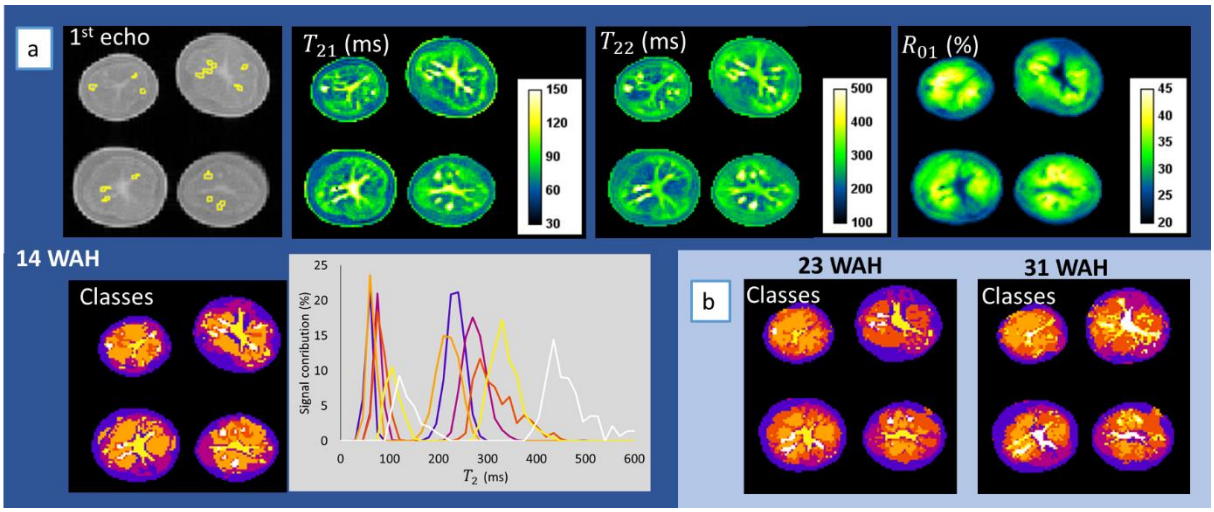

Figure 1: a) At 14 WAH, 1st echo of the MRI images with the ROIs delimitating the defects, estimated relaxation times, T_{21} and T_{22}, and short component ratio, R_{01}, classification result and T_2 distribution for each class b) classification result at 23 and 31 WAH

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