Using the Phase for MR Image Segmentation: Application to the Bone of the Knee

P. Bourgeat[1], P. Stanwell[2], S. Ramadan[2], S. Ourselin[1]

[1]BioMedia Lab, Autonomous Systems Laboratory, ICT Centre, CSIRO, Sydney, NSW, Australia, [2]Department of Magnetic Resonance in Medicine, University of Sydney, Sydney, NSW, Australia

Introduction

In MR, the signal is acquired in K-Space, resulting in a complex image composed of a phase and a magnitude. With a properly chosen pulse sequence, the phase can give information about tissue interfaces, but phase is only defined within the interval $[0, 2\pi]$, and phase unwrapping is required prior to processing. Phase unwrapping is extremely time consuming, especially in 3D, and is prone to errors. As a result, only the magnitude of the complex MRI signal is used for clinical diagnostics, leading to a loss of information which is, and can only be, encoded in the phase of the signal. For example, a closer look at the articular and meniscus cartilages in Fig. 1 shows that the phase is more efficient in separating the two cartilages than magnitude, which is a common problem in cartilage image segmentation. We present a novel method to extract textural information from the phase image without the need of phase unwrapping. The technique was applied for the segmentation of the bone of the knee as a basis for cartilage segmentation of the osteoarthritic knee. This work aims to show the potential benefit in including the phase information in MR segmentation algorithms.

Methods

The images used in this abstract where acquired on a whole-body 3T clinical scanner (Magnetom Trio, Siemens AG, Germany) using the manufacturer's transmit-receive quadrature extremity coil. Raw image data were acquired as a 3D-volume with the use of a simple gradient-echo sequence (FLASH). Raw data was then processed to produce separate phase and magnitude images. Acquisition parameters were chosen to maximise signal-to-noise ratio and minimise susceptibility effects while enhancing the inherent phase contrast of the knee joint. The following acquisition parameters were used : echo times - 4.9 & 8.6 ms, repetition time - 28 ms, flip angle - 15^0, FOV 150 mm, matrix = 256 x 256, 1.5 mm slice thickness, and 64 partitions.

The acquired 3D image I(x, y, z) can be expressed as $I(x, y, z) = A(x, y, z) \cdot e^{j\varphi(x, y, z)}$ where $A(x, y, z)$ is the magnitude and $\varphi(x, y, z)$ the phase of the image. From the complex image, a phase image $I_\varphi(x, y, z) = e^{j\varphi(x, y, z)}$ is generated with amplitude 1, and therefore only composed of phase information. $I_\varphi(x, y, z)$ is a complex image that can be Fourier transformed and then filtered in order to extract phase information without phase unwrapping. We use a bank of Gabor filters [1] which are bandpass oriented filters. Variations in the phase induce variations in the frequency of the signal, and a frequency analysis performed using Gabor filters on $I_\varphi(x, y, z)$ can extract textural information in the phase [2]. The same bank of Gabor filters can be applied on the amplitude $A(x, y, z)$ and the phase image $I_\varphi(x, y, z)$ generating two different sets of features, containing different types of information.

Results and Discussion

The images of nine volunteers' knees were acquired. Four were used for training of a Support Vector Machine classifier [2], and the remaining five were used for testing. In order to test the utility of phase for bone segmentation, the classifier was trained with three different sets of features respectively extracted from the magnitude, phase, and magnitude+phase. We evaluate the segmentation using the Dice Similarity Coefficient (DSC) which is defined as $DSC = 2 \cdot n\{S_M \cap S_A\}/(n\{S_M\}+n\{S_A\})$, where S_M are the sets of voxels manually segmented, and S_A the set of voxels automatically segmented, and $n\{S\}$ is the number of elements of set S. The DSC is a measure of overlap ranging from 0, indicating no similarity to 1, indicating complete agreement. The mean DSC are presented in Table 1 for the 4 training images and the 5 test images. The phase by itself does not give good results as it produces a lot of misclassification in the background. The magnitude produces better features than the phase, but there are misclassifications around the skin and the ligaments. The combination of the features extracted from the phase and the magnitude significantly improves the DSC compared to using the phase or the magnitude only. The training set is robust enough to maintain the DSC to an acceptable level on the testing data. A 3D rendering after Gaussian smoothing of a segmented test image is presented Fig. 2.

Conclusions

We have presented results on bone image segmentation of the knee articulation using both phase and magnitude information. In most conventional anatomical imaging, the phase information is acquired, but is usually not used for diagnostic purposes. The phase image contains extra information that can be used in image segmentation. Gabor filters can efficiently extract this information, which is useful to discriminate bones from surrounding tissues. By using this technique, the future goal is to provide a complete map of the different types of tissues in the knee, and more specifically the cartilage, for use in clinical studies of osteoarthritis.

References:

1. Grigorescu, S., *et al.*.: Comparison of texture features based on Gabor filters. IEEE Trans Image Proc **11** (2002) 1160–1167
2. Vapnik, V.: The nature of statistical learning theory. Springer Verlag, New York (1995)
3. Bourgeat P. , et al..: The use of Unwrapped Phase in MR Image Segmentation: a Preliminary Study. MICCAI 2005, Springer Verlag, lncs 3750, 813-820.

	DSC Train	DSC Test
Phase	0.81	0.77
Magnitude	0.85	0.85
Phase and Magnitude	0.89	0.87

Table 1. Mean DICE coefficient on the bone segmentation on training and test images.

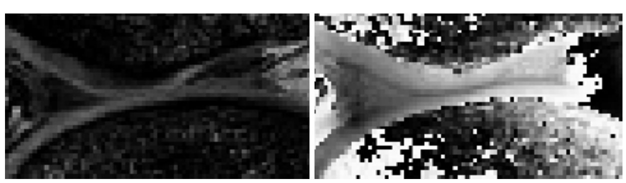

Fig. 1. Magnitude (left) and phase (right) images of the articular and meniscus cartilages.

Fig. 2. 3D rendering of the segmentation results.