The Use of Unwrapped Phase in MR Image Segmentation: A Preliminary Study

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Abstract. This paper considers the problem of tissue classification in 3D MRI. More specifically, a new set of texture features, based on phase information, is used to perform the segmentation of the bones of the knee. The phase information provides a very good discrimination between the bone and the surrounding tissues, but is usually not used due to phase unwrapping problems. We present a method to extract textural information from the phase that does not require phase unwrapping. The textural information extracted from the magnitude and the phase can be combined to perform tissue classification, and used to initialise an active shape model, leading to a more precise segmentation.

1 Introduction

In MRI, the signal intensity, which is normally used for diagnostic purposes, depends upon spin density and relaxation time in order to enhance contrast between different type of tissues inside the body. However, intensity is only one part of the signal. The image acquisition is performed in the K-space [1], resulting in a complex signal, that can be decomposed as a magnitude, and a phase component as shown in Figure 1. Depending on the choice of the pulse sequence, the phase can represent different types of information:

- for angiography, the acquisition sequence is designed to purposefully sensitise the image to phase due to velocity of moving spins and emphasise the motion of blood.
- for conventional anatomical imaging methods, the images are usually displayed in magnitude mode and thus the phase information is not used. In this context the phase information is non-coherent dephasing caused by chemical shift and local magnetic susceptibility.

The latter effect is due to differing magnetic susceptibilities within the body and/or instrumental imperfections. Some imaging sequences are more sensitive

Fig. 1. Magnitude and phase image with $T_E = 10\text{ms}$. The wrapped phase image shows strong textural information in the bone and the background, compared to the relatively smooth areas in the cartilage and the muscles.

Fig. 2. Magnitude and phase image of the knee cartilage

to this effect than others, so the choice of the acquisition methods is very important. With a properly chosen sequence, the phase can give information about tissue interfaces. In the case of the articular cartilage, there is a large difference in magnetic susceptibility between the subchondral bone and the cartilage that creates a local magnetic gradient leading to loss of signal [2]. The study of the phase can give additional information on the cartilage/bone interface due to magnetic inhomogeneities caused by the local tissue transition. A closer look at the femur and tibia cartilage (Figure 2) shows that the magnitude is not efficient in separating the two cartilages. This is a common problem in cartilage segmentation, whereas the phase shows a strong black line between them. Unfortunately, phase is only defined within the interval $[0, 2\pi[$, and phase unwrapping is required prior to processing [3][4]. Phase unwrapping is commonly used in MRI to perform the three points Dixon water/fat separation technique, and to reconstruct cardiovascular structures in phase contrast MRI, but the operation can be extremely time consuming, especially in 3D, and is prone to errors. Moreover, most algorithms can't handle the high level of noise that can be found in

the background for example. As a result, only the magnitude of the complex MRI signal is used for clinical diagnostics. This results in the loss of information which is and can only be encoded in the phase of the signal. More information on phase acquisition can be found in Haacke et al [1].

This paper intends to demonstrate the potential benefit in including the phase information in segmentation algorithms. Since image processing algorithms have been mainly designed to work on magnitude images, the paper also presents the corresponding tools that have been developed to extract useful information from the complex image without the need of phase unwrapping.

2 Method

The images used in this paper were acquired on a Bruker Medspec 4T Whole-body MRI scanner with a specific knee coil. The acquisition was performed on a healthy patient with $(T_R/T_{E1}/T_{E2} = 45/10/20 \text{ ms})$. The scans are made through the sagittal plane with a resolution of $0.5859 \times 0.5859 \times 1.5 \text{ mm}^3$, and a size of $256 \times 256 \times 64$ pixels, which gives two complex images with two different T_E . Increasing the T_E increases the phase difference between the different type of tissues, but also increases the noise level in the magnitude image. As reminded by Ghiglia [3], it is important to note that phase is not a signal itself, but a property of a real signal, and should therefore be processed as such. A complex 3D image $I(x, y, z)$ can be expressed as :

$$I(x, y, z) = A(x, y, z) \times e^{j\varphi(x, y, z)}, \quad (1)$$

where $A(x, y, z)$ is the magnitude of the image, and $\varphi(x, y, z)$ the phase of the image. In areas of low intensity, such as the background, the signal does not contain enough information to produce an accurate measure of the phase, which is mainly composed of noise.

Reyes-Aldasoro and Bhalerao [5] presented a method based on texture analysis to perform 3D segmentation of the bone in MRI. They apply a subband filtering technique, similar to a Gabor decomposition, in the K-space in order to extract textural information from the different type of tissues, but this technique does not take full advantage of the information contained in the phase. The filter is set to select a region of the spatial and frequency domain. The amplitude of the output of the filter measures the signal energy within the selected region. This means that the output of the filter is strongly dependant on the local amplitude of the signal, and within the areas of low amplitude, the phase information will not be taken into account. We first introduced the idea to process the phase information separately from the amplitude information, without phase unwrapping, in the context of image segmentation in digital holography, where complex images are widely available [6]. Instead of applying a bank of Gabor on the complex image only, the same filters can be applied to the phase image after a normalisation step. In order to remove the sensitivity to amplitude variation, the complex image is divided by the amplitude, to generate a complex

image $I_\varphi(x, y, z)$ of constant amplitude equal to 1, and therefore only composed of phase information :

$$I_\varphi(x, y, z) = \frac{I(x, y, z)}{A(x, y, z)} = e^{j\varphi(x, y, z)} = \cos(\varphi(x, y, z)) + j.\sin(\varphi(x, y, z)). \quad (2)$$

$I_\varphi(x, y, z)$ is a complex image that can be Fourier transformed and then filtered in order to extract phase information without phase unwrapping. Variations in the phase induce variations in the frequency of the signal, and therefore, a frequency analysis performed using Gabor filters on $I_\varphi(x, y, z)$ can extract usefull information about the phase. The same bank of Gabor filters can then be applied on both the amplitude image $A(x, y, z)$ and the phase image $I_\varphi(x, y, z)$, generating two different sets of features, containing different types of information.

3 Implementation

In 2D, the Gabor filters [7][8] are defined by their impulse response $h(x, y)$ such that:

$$h(x, y) = g(x, y)e^{j2\pi(Ux+Vy)}, \quad (3)$$

with:

$$g(x, y) = \frac{1}{2\pi\sigma_x\sigma_y}e^{-\frac{1}{2}\left[\left(\frac{x}{\sigma_x}\right)^2 + \left(\frac{y}{\sigma_y}\right)^2\right]}, \quad (4)$$

where $h(x, y)$ is a complex sinusoid of frequency (U, V) with a Gaussian envelop $g(x, y)$ of shape defined by (σ_x, σ_y) . The Fourier transform of $h(x, y)$ is given by :

$$H(u, v) = G(u - U, v - V), \quad (5)$$

with

$$G(u, v) = e^{-2\pi^2\sigma_x\sigma_y(u^2+v^2)}, \quad (6)$$

the Fourier transform of $g(x, y)$. For our implementation, we used a bank of non symmetric Gabor filters with 5 scales and 6 orientations as presented in Figure 3. These parameters were chosen to obtain a good coverage of the frequency space. Because of the anisotropic nature of the images, most of the textural information is contained in the sagittal planes, so we opted for a two dimensional implementation of the Gabor filters. Each magnitude and phase image is Fourier transformed, and multiplied by each Gabor filter $H(u, v)$ corresponding to the different scales and orientations. A 3D Gaussian filter is then applied on the magnitude of the output of each filter to smooth the response across slices. It is important to preserve rotation invariance, since the knee can be in various positions, and more or less bent. Therefore, the magnitude of the output of the filters is summed across all orientations as shown in Figure 4, in order to obtain a set of features that is rotation invariant. Figure 5 presents the features obtained from the magnitude and the phase images with $T_E = 10$ ms. For each dataset, the magnitude of the image is low-pass filtered with the same 3D Gaussian filter to produce an additional feature for the classifier.

Fig. 3. Bank of Gabor filters, with the contour representing the half-peak magnitude of the filter response

Fig. 4. Phase features at scale 5, all 6 orientations are summed together to produce a rotationally invariant feature

Fig. 5. Magnitude features (top row) and phase features (bottom row). The features represent a 5 levels decomposition, from low to high frequencies (presented left to right)

The feature images clearly show how the phase can be used to discriminate the bone from the other tissues, but are not of much utility for separating bone from background. On the other hand, the magnitude can discriminate between the bones and the background, so that the combination of the two sets of features can be used to effectively segment the bones. The pixels are classified using the SVM classifier [9]. The implementation relies on SVMLIB [10]. We use an RBF kernel, with the parameters (C, γ) optimised using a five fold cross validation.

4 Experimental Results and Discussion

A single slice, where the bones have been manually segmented, is used to train the classifier. In order to test the utility of phase for bone segmentation, the classifier was trained with three different sets of features :

- The first set of features is composed of the features extracted from the magnitude, and the low-pass filtered magnitude of the image for the two T_E values.
- The second set of features is composed of the features extracted from the phase, and the low-pass filtered magnitude of the image for the two T_E values.
- The third set of features is composed of the features extracted from the magnitude and the phase, and the low-pass filtered magnitude of the image for the two T_E values.

Since we are looking at segmenting large objects, a size filter is applied to the segmented image in order to remove small misclassified volumes. The sensitivity and specificity results after filtering are presented in Table 1. The phase by itself does not give good results as it produces a lot of misclassification in the background, since the bone and the background have a similar response. 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 maintains the specificity around 97% but increases the sensitivity to 95%, and leads to a global misclassification rate of 3.3%. Moreover, only the combination of the features can successfully separate the four bones present in the image, the two other set of features merging the patella with the femur, and the fibula with the tibia. Slices of the segmented images for each type of feature are displayed in Figure 6, along with a 3D view

Table 1. Sensitivity, specificity, and global misclassification rate on the bone segmentation

	Magnitude	Phase	Magnitude and Phase
<i>Sensitivity (%)</i>	90.3	79.9	95.1
<i>Specificity (%)</i>	97.1	96.0	96.9
<i>Misclassification rate (%)</i>	3.8	6.3	3.3

Fig. 6. Segmentation results with (a) magnitude, (b) phase, (c) phase and magnitude, (d) phase and magnitude 3D view

of the segmented bones using the full set of features. On a 2.8GHz PC, with a C++ implementation of our technique, it took 6 minutes to generate the 22 features, 3 minutes to train the classifier, and 35 minutes to segment the image.

4.1 Discussion

The use of texture to perform segmentations rarely produces results of sufficient accuracy and robustness for medical image analysis. However, it can be used to automatically initialise other advanced segmentation algorithm such as active shape models [11]. Such models are highly dependent upon initialisation, with no accepted ways to initialise them, especially in 3D. The most promising approach relies on a registration of the resulting segmentation to an atlas (or statistical map) which is then used to initialise the active shape models.

To evaluate if the results are accurate enough to initialise a statistical shape model, the location of the centre of mass is measured for each bone in the segmented image, and compared to the manually segmented one. The distances are reported in Table 2. The largest difference is obtained for the patella with 2.8 mm. This difference can be explained by the high level of noise present in this area, produced by the different type of tissues (ligament, fat, skin) surrounding the patella which produce a lot of misclassification. Nevertheless, the position is sufficiently close to be used to initialise an active shape model.

Table 2. Distance to the centre of mass for each type of bone between the manually segmented mask, and the result of the segmentation using features extracted from the phase and the magnitude.

	Femur	Tibia	Patella	Fibula
<i>Distance (in mm.)</i>	0.69	1.07	2.8	1.72

5 Conclusion

In this paper, we have presented preliminary results on bone segmentation of the knee articulation using both phase and magnitude information. In most con-

ventional 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 easily 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 type of tissues in the knee, and more specifically the cartilage, for use in clinical studies of osteoarthritis.

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