ROBUST SPATIAL PHASE UNWRAPPING FOR ON-LINE MR-TEMPERATURE MONITORING

B. Denis de Senneville[1], *G. Maclair*[1,2], *M. Ries*[1], *P. Desbarats*[2], *B. Quesson*[1], *C. T. W. Moonen*[1]

[1] IMF, CNRS/Université Bordeaux 2 - 146, rue Léo Saignat, F-33076 Bordeaux
[2] LaBRI, UMR 5800 CNRS/Université Bordeaux 1 - 351, cours de la Libération, F-33405 Talence
{baudouin,maclair,ries,quesson,moonen}@imf.u-bordeaux2.fr - desbarats@labri.fr

ABSTRACT

Magnetic Resonance (MR) systems can be used to monitor temperature changes in and around a treated region during an hyperthermic ablation procedure. Dynamic temperature monitoring allows on-line prediction of cellular destruction during the intervention. MRI systems associate each volume unit with a complex number. Phase component is 2π-periodic (it is a function of the wrapped phase) and accounts for noise sources present in MR imaging. Robust spatial phase unwrapping is a necessary prerequisite for several applications. This study proposes a spatial phase unwrapping algorithm for MR images, allowing a real time implementation for on-line temperature monitoring.

***Index Terms*—** Magnetic Resonance Imaging, Signal processing, Real time systems, Temperature control.

1. INTRODUCTION

Local thermal therapies are increasingly clinically used for tissue ablation [1] [2]. In order to improve the therapeutic efficiency and the safety of the intervention, mapping of temperature and thermal dose appear to offer the best strategy to optimize such interventions and to provide therapy endpoints. On-line availability of dynamic temperature mapping allows prediction of tissue necrosis during the intervention based on semi-empirical thermal dose calculations [3]. Of the different imaging modalities, Magnetic Resonance Imaging (MRI) appears the ideal tool for temperature mapping. Much progress has been made recently in MR thermometry research, and some applications are appearing in the clinic. A particular advantage of MRI for guiding thermal procedures is that MRI not only allows temperature mapping but it can also be used for target definition.

The MR observable signal is a complex number. Grey levels on anatomical images are proportional to the magnitude value whereas phase value relates the proton resonance frequency. The most widely used MR temperature mapping is based on temperature dependence of the water proton resonance frequency (PRF) [4]. The temperature map at instant n (noted ΔT_n) can be obtained on-line by analyzing signal variation between the current phase image φ_n and a reference phase image φ_{ref} acquired before the hyperthermia (typically the first of the temporal serie φ_0) as follow :

$$\Delta T_n = (\varphi_{ref} - \varphi_n) .k \qquad k = \frac{1}{\gamma.\alpha.B_0.T_E} \tag{1}$$

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where γ is the gyromagnetic ratio ($\approx$ 42.58 MHz/Tesla), α the temperature coefficient ($\approx$ 0.009 ppm/K), T_E the echo time and B_0 the main magnetic field. This calculation is performed for each voxel to obtain temperature maps.

Phase wraps often occur on organ regions with presence of large susceptibility variations [5]. During on-line thermometry intervention, robust phase unwrapping plays a very important role :

- in the creation of sensivity maps required for a sensitivity encoding (SENSE) reconstruction [6], which is very usefull to reduce considerably scan time,
- in several implementations for distortion compensation of echo planar images [7],
- for a number of image processing requiring phase signal intensities of a given pixel and its neighbours (spatial transformation application or filtering for example [8]).

Phase unwrapping has typically to cope with images of low resolution (compared to the spatial variation of a phase jump), low SNRs and also discontinuous data sets.

To allow on-line monitoring of temperature, phase unwrapping for each image of the time series must be performed under the following conditions:

- Real time implementation : unwrapping of an image must be fast in order to be done in the interval of time between two successive acquisitions (approximatively 30 ms and 60 ms for images of resolution 64×64 pixels and 128×128 pixels respectively) to ensure on-line monitoring of temperature evolution. In addition, computation time must not vary with the phase wraps complexity, preventing the use of iterative optimization schemes. A maximal computation time must be known for a specific image resolution.
- No user calibration of the algorithm for the observed organ.

Several algorithms have been proposed in the litterature for various applications (radar, interferometry, ...) and a good overview of phase unwrapping can be found in Chavez et al [9]. Phase unwrapping approaches belong mainly to one of the following classes: path following [10], minimum L^p norm [11], Bayesian/regularization [12], and parametric modelling [13]. Although the majority of phase unwrapping methods lead to satisfying results on coherent MRI-datasets with large SNR and sufficient spatial resolution [14], they have commonly problems to cope with severely under-sampled or degraded datasets which are typically obtained by fast imaging methods with long echo times. In addition, time computations required are generally not compatible for an on-line implementation.

Spatial phase unwrapping performed with a region growing based algorithm was found to be very low time consumming as each pixel is visited only one time. However, the major drawback is that an error made in one pixel is propagated on pixels observed thereafter. This study proposes a robust automatic region growing based phase unwrapping algorithm for on-line temperature monitoring exploiting the information given by the two complex components of the MR signal.

2. METHOD DESCRIPTION

An assumption taken by most phase unwrapping algorithms is that the absolute value of phase differences between neighbouring pixels is less than 2π. If this assumption is not violated, the absolute phase can be easily determined, up to a constant. This condition might be violated if the true phase surface is discontinuous, or if the wrapped phase is noisy. In either cases, phase unwrapping becomes a very difficult problem. The proposed approach consists of using magnitude intensity of the MR signal as a quality criterion in order to :

1. Perform an oriented region growing algorithm supporting firstly neighbouring pixels with the smallest phase uncertainty.
2. Improve computation time by restricting phase unwrapping to regions having a sufficient signal to estimate an accurate phase value.

2.1. Evaluation of a quality criterion on MR phase signal using magnitude images

The accuracy of MR thermometry depends on several factors such as signal-to-noise ratio (SNR), echo time, field strength, artifacts. Acceleration of image acquisition [15] in order to increase temporal resolution usually implies a SNR reduction. It is well established that electronic noise is Gaussian white noise [16]. The MR system measures the real and imaginary components of the signal. As these two data each contain (ideally) Gaussian white noise, the resulting noise in the magnitude images will have a Rician distribution [17] [18]. In addition, biological noise and potential noise generated by the heating device can also hamper image quality. SNR can be evaluated on-line on magnitude images as follow :

$$SNR = \frac{M}{\sigma_G} = \frac{M}{\sigma_R \times 1.53} \tag{2}$$

where M is mean pixel intensity in a region where sufficient signal is measured, σ_G and σ_R are Gaussian and Rician noise standard deviations respectively. respectively (σ_R can be computed in a region where no signal is available). Those two regions of interest are manually defined before the intervention by the user.

Phase uncertainty can be related to SNR with the following expression [20] :

$$\sigma(\varphi) = \frac{1}{SNR} \tag{3}$$

It is also well-established that magnitude signal is decreased in voxels containing phase wraps higher than 2π [19]. Phase uncertainty is thus directly linked to magnitude signal. Indeed, temperature computation may be artifacted for voxels with low magnitude intensity (since in region without signal, phase value may take any value between 0 and 2π).

2.2. Proposed region growing algorithm

The first idea of the proposed approach consists of using magnitude signal to perform an oriented region growing algorithm supporting firstly neighbouring pixels with the smallest phase uncertainty. In principle, the fully automated algorithm works as follow :

1. A germ is placed in the pixel with the highest magnitude signal intensity.
2. Neighbouring pixel in 4-connexity with highest magnitude signal is selected.
3. Spatial phase gradients between the initial pixel and this neighbour is computed.
4. 2π is then either added if this gradient is higher than π or subtracted if the gradient is lower than $-\pi$.

This process is repeated until all pixels are visited.

2.3. Signal intensity threshold filter

To improve computation time, the second idea of the proposed approach is to analyze the MR-signal for each pixel of the acquired images in order to restrict phase unwrapping to regions having a sufficient signal to estimate a correct phase value and thus an accurate temperature measurement.

The precision of temperature estimation can be estimated from the standard deviation of a time series of measurements. As temperature variation is proportional to a phase variation, noise on the measured temperature can be evaluated with:

$$\sigma(\Delta T) = \sqrt{\sigma^2(\varphi_{ref}) + \sigma^2(\varphi_n)}.k \tag{4}$$

By assuming that noise is equally distributed in phase images ($\sigma(\varphi_{ref}) = \sigma(\varphi_n) = \sigma(\varphi)$), we obtain:

$$\sigma(\Delta T) = \sigma(\varphi).\sqrt{2}.k \tag{5}$$

A binary mask, selecting voxels with sufficient signal for temperature computation can be obtained by thresholding magnitude images. This threshold may depend on many parameters (the observed organ, the acquisition sequence used, etc...) and cannot be arbitrarily defined. A possible approach consists of computing this threshold by making a statistical SNR analysis. Combining equations 3 and 5 it can be obtained that theoric temperature uncertainty $\sigma(\Delta T)$ can be linked to SNR with:

$$\sigma(\Delta T) = \frac{\sqrt{2}.k}{SNR} \tag{6}$$

A validity range for the signal can be constructed by thresholding magnitude images with a threshold M_T determined from an acceptable uncertainty on temperature, computed with:

$$M_T = \frac{\sigma_R.1.53.\sqrt{2}.k}{\sigma_{max}(\Delta T)} \tag{7}$$

where $\sigma_{max}(\Delta T)$ is the maximal acceptable standard deviation on temperature defined by the user ($\sigma_{max}(\Delta T) = 2^oC$ for instance). When too many pixels do not match the validity range, the user can either optimize the acquisition sequence parameters to increase the SNR or adjust the value of the threshold $\sigma_{max}(\Delta T)$, accepting a reduction of temperature precision.

3. EXPERIMENTAL VALIDATION

All images were obtained on a 1.5 Tesla Philips Intera Achieva system with a conventional gradient echo sequence. Echo time was set to 50 ms. A rectanguler field of view of size 230 mm and a slice thickness of 5 mm were used.

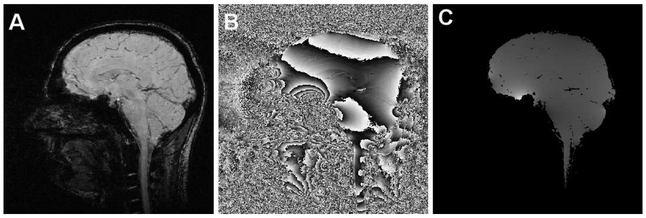

Fig. 1. Sagital high resolution image of a human head used to create a reference spatial unwrapped phase image - A : anatomical image, B : phase image, C : reference spatial unwrapped phase image (B) unwrapped with the proposed algorithm.

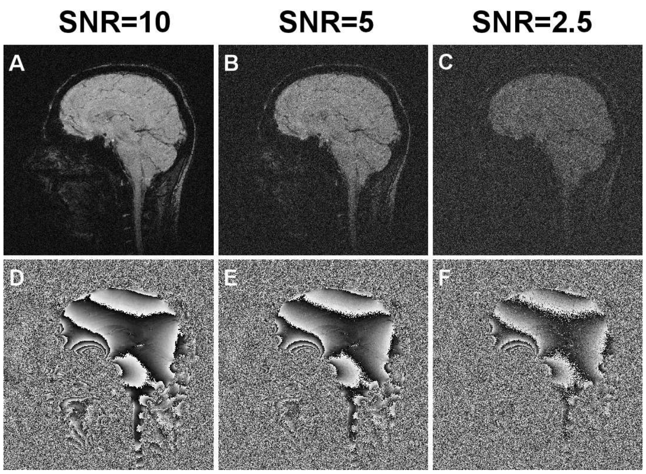

Fig. 2. MR images of Figure 1 with simulated additional Gaussian noise to the complex data - **Up :** anatomical images, **Down :** corresponding wrapped phase images.

The presented images show the wrapped and the unwrapped phase maps of a human head as an typical example of the comparison (see figure 1). The regions close to the sinus cavities show strong local B_0 inhomogenities, which lead to a high rate of phase wraps.

The algorithm created a reference unwrapped phase map from a high resolution (0.5 mm in plane) and high SNR (higher than 50) dataset (see figure 1.C).

Resolution (pixels)	**Unwrapping on all pixels (ms)**	**Signal intensity threshold filter (ms)**
512×512	10389	465
256×256	603	36
128×128	42	5
64×64	4.7	0.8

Table 1. Computation time.

Low SNRs and spatial undersampling lead to incorrect phase estimates which are evaluated on show error maps reported on Figures 3. Those error maps are constructed using the mean absolute phase deviation from the reference phase.

The robustness against low noise levels was investigated by adding additional a Gaussian noise to the complex data in a separate postprocessing step, in order to achieve a series of images with an SNR of 10, 5 and 2.5 (see Figures 2.A to 2.H).

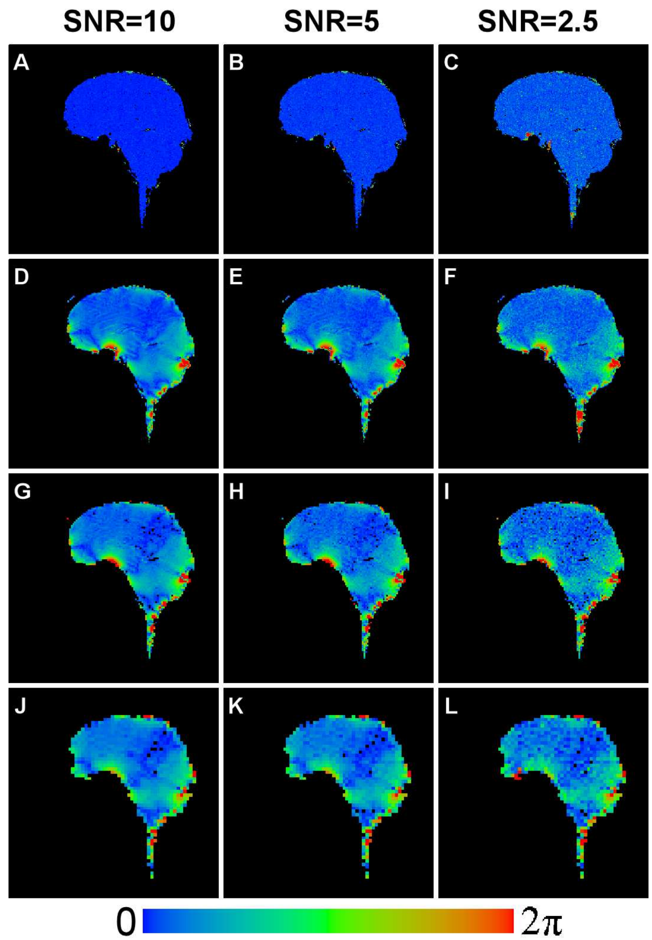

Fig. 3. Absolute error maps between unwrapped phase images and reference unwrapped phase image reported on figure 1.C for different SNR value and different image resolution (First row : 512×512 pixels, Second row : 256×256 pixels, Third row : 128×128 pixels, Fourth row : 64×64 pixels).

Spatial undersampling of areas with a high rate of phase wraps complicates a correct phase estimate. To investigate the influence of spatial undersampling of phase wraps on the proposed algorithm, high resolution data was obtained and lower resolutions were realized by digital down-sampling in Fourier space as a post-processing step. The following matrix sizes are thus obtained : 512×512, 256×256, 128×128 and 64×64.

The algorithm have been implemented in C++ and Table 1 reports computation time obtained for different image resolutions on our test plateform (AMD Athlon 3400+ with 1 Go of RAM). The left column gives an upper bound on computation time as the proposed region growing algorithm is performed on the whole image, whereas the right column shows the computation time when the signal intensity threshold filter is applied.

4. DISCUSSION AND CONCLUSION

Results obtained demonstrated that the proposed algorithm is fully stable to noise as unwrapping errors were observed only on high resolution images with SNR lower than 5 (see Figure 3.C). It can also be observed that in areas of severe spatial undersampling, like in the vicinity of the sinus cavities, the algorithm have problems to reconstruct the correct phase. This is due to the fact that the fundamental condition that phase variation cannot by be higger than 2π is violated. However, it is shown that the proposed algorithm isn't likely to propagate these errors to normally well behaved regions as magnitude signal is decreased in voxels containing phase wraps higher than 2π [19].

This study demonstrated the importance of the magnitude information for phase unwrapping problem in magnetic resonance imaging :

- To improve the robustness by preventing errors propagation in region growing algorithm. The proposed approach is very well adapted to MR images as magnitude signal information is used to provide a quality criterion on phase measurement in order to observe firstly pixels allowing reliable unwrapping. This stability has a special importance in regions with strong B_0 inhomogeneity, such as the caudal brain or areas inside or near tumors.
- To reduce considerably computation time by limiting the number of observed pixels using a quality criterion set on temperature accuracy, preventing any user calibration to the observed organ.

Another advantage of this approach is that the computation time only depends on image resolution and doesn't vary with the number of phase wraps present and the noise level. Computation can typically found between 465 ms for a 512×512 dataset and less than a millisecond for 64×64 images. Performances obtained are thus fully compatible with a real time implementation for on-line temperature monitoring.

Currently, our algorithm is implemented for two-dimensional image but could be extended to unwrap three-dimensional data sets when technological progress in rapid MR thermometry protocol will allow on-line acquisition of 3D volumes.

It is also important to note that this algorithm is not restricted to computation of MR thermometry and have succesfully be adapted to remove artifacts related to phase wrapping on MR venography [21].

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