PCA-BASED IMAGE REGISTRATION : APPLICATION TO ON-LINE MR TEMPERATURE MONITORING OF MOVING TISSUES

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ABSTRACT

Real-time Magnetic Resonance (MR) thermometry provides continuous temperature mapping inside the human body and is therefore a promising tool to monitor and control interventional therapies based on thermal ablation. Temperature information must be mapped to a reference position of observed organs in order to allow thermal dose computation, as the history of temperature is required for each pixel. Motion compensated MR-thermometry for thermotherapy has to cope with Radio-Frequency (RF) artifacts and relaxation-time changes of the monitored tissue. While purely optical-flow-based realignment may lead to temperature map computation errors for the case of local or global intensity changes, Principal Component Analysis based realignment results in accurately registered temperature maps.

The motion estimation process described in this paper consists of two steps : a parameterized flow models is initially computed using a principal component analysis during a preparative learning step; during the intervention, motion is characterized with a small set of parameters using a least square solver.

Index Terms— Magnetic Resonance Imaging, Real-time, Temperature control, Motion compensation, Principal Component Analysis

1. INTRODUCTION

Real-time MR-thermometry provides continuous temperature mapping inside the human body and is therefore a promising tool to monitor and control interventional therapies based on thermal ablation carried out with help of radio-frequency, laser, cryogenics or focused ultrasound (FUS) [1].

The magnitude of the observable MR signal is directly proportional to the tissue density while the phase is proportional to the temperature of the observed tissue. Therefore, comparing the phase of a dynamic MR imaging to a reference phase (for example the first of the series) permits the calculation of the relative temperature difference [2].

Unfortunately, temperature variations are not the only contributing factors to phase changes of the MR signal. Motion of the observed tissue in imperfect magnetic fields and susceptibility variations between different tissues also alter the phase of the MR signal [3]. Therefore, a robust removal of these non-temperature related phase variations is a prerequisite for precise MR-thermometry on moving objects.

Several approaches have been proposed in the past such as modeling of the motion induced phase changes [4], artefact estimation by extrapolation from areas not affected by temperatures changes [5] and phase correction tables [6]. The latter approach is motivated by the fact that for most therapeutic applications within the human body, motion is caused by the respiratory or the cardiac cycle and is thus periodic. This can be exploited by establishing a phase lookup-table prior to MR-thermometry which covers the entire motion cycle. Subsequently, during MR-thermometry, for a given organ position the corresponding phase correction is selected and subtracted from the current phase. Since the difference represents only temperature related phases changes, the correct temperature can be estimated.

Thus, temperature evolution allows on-line thermal dose evaluation during the intervention, which in turn permits an accurate and immediate prediction of tissue necrosis. The thermal dose can be compute as the integral over time of the temperature during the hyperthermia procedure [7]. In order to calculate the thermal dose, motion during the intervention has to be compensated.

In the past, several techniques have been suggested to estimate organ displacement, for example navigator echoes [8] (the estimated motion information is restricted to translational motion) or ultrasonic echoes [9] (the estimated motion information is restricted to knowledge outside the heating zone because of the echo perturbation induced by the temperature rise), or by means of image processing.

For the latter, a 3D image registration would be required. However, in practice it is possible for respiratory induced motion to choose the imaging plane direction parallel to the principal axis of the organ displacement and thus reduce the problem to two dimensions.

Although organ displacement estimation can be addressed by any established 2D image registration method, the complexity of the periodical motion patterns in the abdomen are poorly described with global parametric affine linear models. Optical-flow based image registration methods obtain the complex displacement of image components on a pixel-by-pixel basis [10] and are thus more suitable for realignment.

However, optical-flow based algorithms rely on the assumption of conservation of pixel value along the trajectory. This condition can be violated during thermotherapy. Since tissue is heated, several MR relevant tissue properties such as T_1 and T_2 relaxation times can change during imaging [11]. This leads to local intensity variations, which in turn can be interpreted by optical-flow based algorithms as “false motion”. In addition, potential global intensities variations can be generated by the heating device. This makes optical-flow based image registration less robust compared to affine models

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which rely on a global fit of the image content and are thus less susceptible to local intensity variations.

The objective of this paper is to propose a robust registration algorithm to estimate periodical motion from anatomical images in real-time, in order to correct errors generated by organ displacements on thermal dose maps.

In order to fulfill the real-time condition, the entire processing of an image must be done in the interval of time between two successive acquisitions (approximatively 140 ms for one image of resolution 128×128 pixels for instance) to ensure on-line monitoring of temperature evolution.

2. METHOD DESCRIPTION

During the hyperthermic intervention, local and global intensity modifications on MR-magnitude images may be generated not only by displacement of the image content, but also by cellular destruction and artifacts generated by the heating device. Since optical flow based realignment would also interpret the latter as motion, the proposed approach is to learn motion patterns based on optical flow analysis from images acquired during a preparative learning step performed before hyperthermia. Subsequently, Principal Component Analysis (PCA) is used to find the eigenvectors of the observed set of flow fields [12]. In the scope of this paper, we refer to these eigenvectors as basis flows. Then, during hyperthermia, individual flow fields are represented as a linear combination of the basis flows. The coefficients of the linear combination are estimated using a Marquardt-Levenberg least square solver. This provides a flow field that is consistent with the learned model and robust under the assumption of global brightness constancy but allows local intensity variations.

2.1. Estimation of organ displacement during the preparative learning step

The training set from which we learn a model of image motion is a set of n flow fields. The objective is to relate the coordinate of each part of tissue in the image with the corresponding part of tissue in a reference image. In this study, the reference image is chosen to be the first of the time series. In general, motion estimated on anatomical images can be obtain by a variety of image registration algorithms [10]. However, registration efficiency is related to the nature and domain of the transformation to detect (global [13] [14] or local [15] [16] transformation). A compromise has thus to be found between the permissiveness of the spatial transformation T and the robustness of the estimation process. For strong motion amplitude, well-adapted technique consists of using results obtained with a global transformation estimation as a starting point for a local transformation estimation. To estimate organ displacement prior hyperthermia, a global affine transformation is estimated in a first step, using a differential approach of Gauss-Newton algorithm [13]. In a second step, a hierarchical approach of Cornelius and Kanade algorithm [15] provides a good estimation of local organ displacements because of the regularity constraint assuming that motion field vectors have similar values for adjacent pixels matching real organ motion. Cornelius and Kanade technique requires an intensity conservation between compared images and a regular displacement between adjacent pixels, resulting in minimization of the expression:

$$\int_y \int_x \Big(\left[I_x u + I_y v + I_t \right]^2 + \alpha^2 \left[\|\nabla u\|_2^2 + \|\nabla v\|_2^2 \right] + \beta^2 \|\nabla w\|_2^2 \Big) \, dxdy \quad (1)$$

where u and v are displacement vectors, $w = \frac{dI}{dt}$, and I_x, I_y, I_t are the partial derivative of the intensity, and α and β is a user defined weighting factor. This minimization problem can be numerically solved with an iterative scheme like Gauss-Seidel.

The length of the preparation step has to be determined to cover an entire motion period of the observed organ. For example, for the case of abdominal MRI sequences, according to the fact that a respiratory period is around 4 seconds, and dynamic acquisition time about 0.1 second, preparation step has to contain at least 100 images.

2.2. Learning parameterized flow models

At this point, we have a model of image motion which is a set of n optical flow fields (n is the length of the preparation step). These fields will be used to build a parameterized flow model. For an image i of size s pixels, each flow field F_i contains $2s$ quantities, since a displacement vector is decomposed in two elements, one for horizontal displacement ($u(x,y)$), one for vertical displacement ($v(x,y)$). For each flow field, we place the $2s$ values as a line of a learning motion matrix of $2s$ x n dimensions (noted F).

Subsequently, PCA is used to find an orthonormal basis that spans an n-dimensional vector space [17]. The components of this basis can be interpreted as the under-laying characteristic patterns of the motion cycle. Since data sets from coherent periodical motion cycles have typically a high degree of redundancy, PCA is a convenient way to reduce the dimensionality n of the the basis. A way to quantify redundancy is to compute the covariance between each pair of variables.

$$Cov(F) = \begin{pmatrix} Cov(F_1,F_1) & \cdots & Cov(F_1,F_n) \\ \vdots & \ddots & \vdots \\ Cov(F_n,F_1) & \cdots & Cov(F_n,F_n) \end{pmatrix} = \frac{1}{2s-1} F F^T \quad (2)$$

Let S be the re-representation of the original data set F. PCA makes the assumption that $S = \{s_1, \cdots, s_n\}$ is a linear combination of F and we note $P = \{p_1, \cdots, p_n\}$ the linear transformation :

$$S = PF \quad (3)$$

Each vector of S is the projection of the corresponding vector of F on to the $\{p_1, \cdots, p_n\}$ basis and the row vectors $\{p_1, \cdots, p_n\}$ are called the principal components of the data.

As redundancy wanted to be eliminated from final data representation, each variable must be as uncorrelated as possible with the other variables. Thus, the covariance matrix of S should have maximized diagonal elements and zero off diagonal terms.

The S matrix can be described as:

- $S = PF$, P being an orthonormal matrix
- $Cov(S) = \frac{1}{2s-1} S S^T$ is a diagonal matrix

The unknown of the problem being P, the covariance matrix formula in terms of P has to be expressed as follow:

$$Cov(S) = \frac{1}{2s-1} S S^T = \frac{1}{2s-1} P A P^T \quad (4)$$

with $A = F F^T$. A is symmetric, so we have $A = EDE^T$, E being the matrix of the orthonormal eigenvectors of A, and D a diagonal matrix. Let P be the transpose of matrix E:

$$Cov(S) = \frac{1}{2s-1} D \quad (5)$$

The rows of P constitute the principal components of F and by choosing the basis of projection such that its vectors are the orthonormal eigenvectors of A, the correlation between the variables of the projected configuration is minimized. Moreover, the i^{th} diagonal term of $Cov(S)$ represents the variance of F along the i^{th} principal component. In order to reduce the dimensionality of the original data set, we will conserve only the k eigenvectors B_k associated to the k largest eigenvalues λ_i in order to preserve the representative patterns of the observed motion. The size k of our subset is obtained by selecting only a subset of the highest ranked components which accounts for more than 95% :

$$\sum_{i=0}^{k} var(\lambda_i) \geq 95\% \tag{6}$$

with

$$var(\lambda_i) = \lambda_i^2 / \sum_{j=0}^{n} \lambda_j^2 \tag{7}$$

2.3. Estimation of motion parameters during the intervention

During the intervention, the approximated spatial transformation T_t between anatomical image acquired at instant t (noted I_t) and the reference image (noted I_0) is a linear combination of the first k basis B_i previously computed:

$$T_t = \sum_{i=0}^{k} C_i B_i \tag{8}$$

where C_i are the parameters of the model to be estimated.

The objective is to find the coefficients C_i that produce a flow field minimizing the following expression :

$$LS = (I_0 - T_t(I_t))^2 \tag{9}$$

This minimization is computed using a Marquardt-Levenberg least square solver [18].

3. RESULTS

We simulated periodic organ displacement of an amplitude of 23 mm peak-to-peak and a period of 3.8 seconds by mounting 600g of calf liver was mounted on a motorized platform. An in-house developed bipolar Radio-Frequency (RF) ablator were used for thermal-ablation. Dynamic MR temperature imaging was performed on a Philips Achieva 1.5 Tesla with a dual-shot gradient recalled EPI sequence. Echo time and repetition were set to 13 ms and 70 ms, respectively. A single slice with an acquisition matrix of 128×128 voxels and a voxel size of $1.5 \times 1.5 \times 5$ mm^3 was acquired each 140 ms. During the preparative learning step, one hundred images were acquired to allow a precise sampling of the periodical motion. Then, the tissue has been heated with 20 Watts of RF-power during 50 seconds.

Figure 1.A and 1.B show a snapshot of the temperature distribution after 30 seconds of radio-frequency heating. The red color coding depicts the heated region around the two electrodes of the RF heating device. In figure 1.A, the temperature image registration is performed in both steps, preparation and heating, by the optical flow based image registration. Note the deformation of the left heated area. Figure 1.B, shows the same data registered with the proposed PCA-based approach which uses optical flow only during the preparation phase. Figure 1.C and 1.D show the corresponding thermal

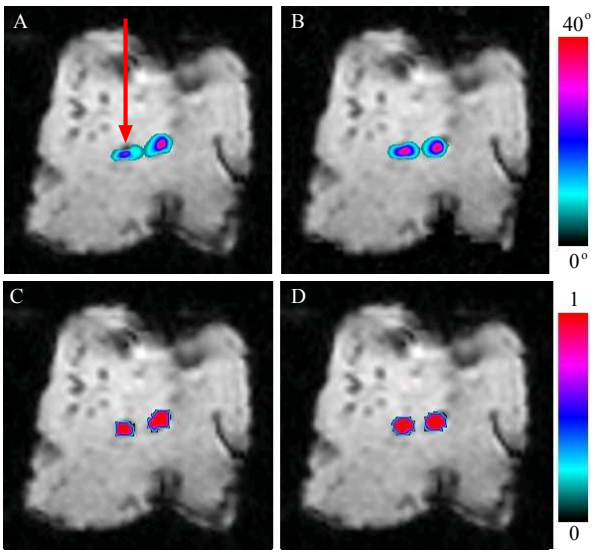

Fig. 1. Temperature (A & B) and thermal dose (C & D) maps obtained on an ex-vivo calf liver submitted to a periodical translation motion after 30 second of bipolar RF heating. A & C : motion is estimated with the classic Cornelius and Kanade algorithm, B & D : motion is estimated with the proposed PCA-based approach.

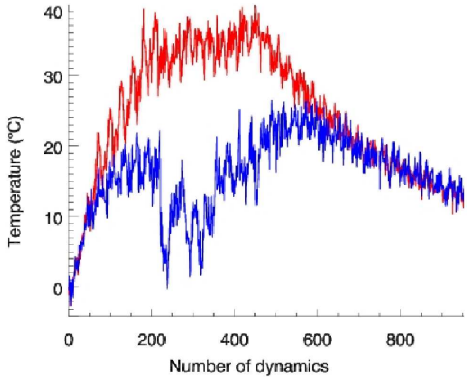

Fig. 2. Temperature temporal evolution in a pixel located in the heated area (red arrow on figure 1.A). Blue curve : temperature is registered with the classic Cornelius and Kanade algorithm, Red curve: temperature is registered with the proposed PCA-based approach.

dose maps obtained. Pixels in which cellular destruction have been achieved are reported in red. It can be observed that only temperature maps registered using the proposed PCA-based realignment leads to accurate thermal dose estimation, which permits in turn a correct evaluation of the lesion. Figure 2 shows the temperature evolution of the area indicated by the red arrow in figure 1.A. The lower curve depicted temperature obtained with the classic Cornelius and Kanade realignment, the upper curve corresponds to the temperature evolution for the same data realigned with PCA. The distortion of the hot-spot in figure 1.A demonstrates the effect of local intensity variations due to heating on the optical-flow based image registration. Since the condition of conserved image intensity is violated, miss-registration occurs. This miss-registration can lead to incorrect

measures of the temperature evolution if a fixed point of interest is observed, as shown in figure 2. Furthermore, the condition of conserved image intensity also leads to a decreased robustness against interference artifacts (not shown), which occur frequently on magnitude images during high power RF or FUS-ablation. This can bias the normalization of the image and thus leads to a complete failure of image registration. The proposed PCA-based method performs well even on images with local intensity variations or image artefacts since it requires neither a conserved image intensity nor a normalized magnitude image, but rather relies on a global fit of the principal components.

4. DISCUSSION AND CONCLUSION

Motion compensated MR-thermometry for thermal therapy has to cope with RF-artifacts and relaxation-time changes of the monitored tissue. While purely optical-flow-based realignment may lead to temperature map computation errors for the case of local or global intensity changes, PCA-based realignment can give for the case of periodical motion accurately registered temperature maps, since it relies on a global fit of the principal components.

Furthermore, for applications which require real-time image registration, PCA-based image realignment has computational advantages, since the reduction of complex periodic motion patterns to the most significant principal components reduces the degrees of freedom for the registration without a priori assumptions or simplifications of the form of the motion.

The estimated coefficients of the model provide a good description of the complex organ deformation and open/facilitate several perspectives for applications, for example :

1. Real-time MR-controlled tissue ablation of moving organs using a fully extra corporal heating source [19] (for example a focused ultrasound device [20]).
2. The possibility to reduced the dimensionality of the observed motion patterns with help of PCA facilitates the correlation with the readings of external sensors such as respiratory gating sensors, electro-cardiograms or navigator echoes.

5. REFERENCES

[1] Dodd G. D., Soulen M. C., Kane R. A., Livraghi T., Lees W. R., Yamashita Y., Gillams A. R., Karahan O. I., and Rhim H., Minimally invasive treatment of malignant hepatic tumors: at the threshold of a major breakthrough, Radiographics 20 (1):9-27, 2000.

[2] Quesson, B., J.A. de Zwart, and C.T. Moonen, Magnetic resonance temperature imaging for guidance of thermotherapy, J Magn Reson Imaging, 2000;12:525-533.

[3] De Poorter J., Noninvasive MRI thermometry with the proton resonance frequency method: study of susceptibility effects, Magn Reson Med 1995;34(3):359-67.

[4] Salomir R, Denis de Senneville B, Moonen CTW. A fast calculation method for magnetic field inhomogeneity due to an arbitrary distribution of bulk susceptibility, Concepts in Magnetic Resonance 2003, Vol. 19B(1):26-34.

[5] Rieke V, Vigen KK, Sommer G, Daniel BL, Pauly JM, Butts K., Referenceless PRF shift thermometry, Magn Reson Med 2004;51(6):1223-31.

[6] Denis de Senneville B., Quesson B., Desbarats P., Salomir R., Palussière J., Moonen C. T. W., Atlas-Based Motion Correction For On-Line MR Temperature Mapping, IEEE, ICIP 2004 Singapore, vol. III, 2571-2574.

[7] Sapareto S. A., Dewey W. CL, Thermal dose determination in cancer therapy, Int. J. Radiation Oncology Biol. Phys. 10, 787-800, 1984.

[8] de Zwart J. et Al. On-Line Correction and Visualiszation of Motion During MRI-Controlled Hyperthermia, Magnetic Resonance in Medicine, 2001; 45:128-137.

[9] Pernot M., Tanter M., Fink M., 3D Real-time Motion Correction in High Intensity Focused Ultrasound Therapy, Ultrasound Medicine and Biology 2004.

[10] Zitova B., Flusser J., Image registration methods: a survey, Image and Vision Computing, 21:977-1000, 2003.

[11] Graham S. J., Bronskill M. J., Henkelman R. M., Time and temperature dependence of MR parameters during thermal coagulation of ex vivo rabbit muscle, Magn Reson Med 1998;39(2):198-203.

[12] Black M.J., Yacoob Y., Jepson A.D., Fleet D.J,Learning parameterized models of image motion, IEEE Proc. Computer Vision and Pattern Recognition, 561-567, 1997.

[13] Friston KJ, Ashburner J, Frith CD, Poline JB, Heather JD and Frackowiak RSJ., Spatial registration and normalisation of images, Human Brain Mapping. 2:165-189, 1995.

[14] Wolberg G, Zokai S., Robust Image Registration Using Log-Polar Transform, Department of computer Science, City College of New York, 2000.

[15] Kanade T., Cornelius N., Adapting optical-flow to measure object motion in reflectance and x-ray image sequences, Association for Computing Machinery, SIGGRAPH/SIGART:pp.50-58, 1983.

[16] Lucas B and Kanade T., An iterative image registration technique with an application to stereo vision, In Proceedings of the International Joint Conference on Artificial Intelligence, pp. 674- 679, 1981.

[17] Shlens J., A Tutorial on Pricipal Component Analysis, www.snl.salk.edu/∼shlens/, 2005.

[18] Marquardt D., An Algorithm for Least Squares Estimation on Nonlinear Parameters, SIAM J. APPL. MATH.11, 431-441, 1963.

[19] Denis de Senneville B., Mougenot C., Desbarats P., Moonen C. T. W., On-Line Mobile Organ Tracking For Non-Invasive Local Hyperthermia, IEEE, ICIP 2006; Atlanta, 2845-2848.

[20] Hacker A., Michel M. S., Marlinghaus E., Kohrmann K. U., and Alken P., Extracorporeally induced ablation of renal tissue by high-intensity focused ultrasound, BJU.Int. 2006;97 (4):779-785.