Radial Basis Function Interpolation for Referenceless Thermometry Enhancement

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Abstract. MRgFUS (Magnetic Resonance guided Focused UltraSound) is a new and non-invasive technique to treat different diseases in the oncology field, which uses Focused Ultrasound (FUS) to induce necrosis in the lesion. Temperature change measurements during ultrasound thermo-therapies can be performed through magnetic resonance monitoring by using Proton Resonance Frequency (PRF) thermometry. It measures the phase variation resulting from the temperature-dependent changes in resonance frequency by subtracting one phase baseline image from actual phase. Referenceless thermometry aims to reduce artefacts caused by tissue motion and frequency drift, fitting the background phase outside the heated region. The aim of this contribution is to propose a novel background phase reconstruction method using Radial Basis Function (RBF) interpolation. The effectiveness of the method has been demonstrated by comparing it against the classical PRF shift and polynomial referenceless approach. The comparison evaluates temperature rises in uterine fibroids during MRgFUS treatments on a set of 10 patients.

Keywords: Radial Basis Function, Interpolation, Referenceless Thermometry, Artificial Neural Network, MRgFUS.

1 Introduction

Hyperthermia is a type of clinical treatment in which body tissues are exposed to high temperatures that can kill pathological lesion, like uterine fibroids [2]. In MRgFUS treatments [7][8], high temperatures are applied on local and small areas by using ultrasound beams that deliver energy to heat the tumour. MRgFUS treatment is performed using the ExAblate 2100 equipment (InSightec, Haifa, Israel), integrated with a Signa HTxt MR scanner (GE Medical Systems, Milwaukee, WI). Thermal ablation of fibroids tissue is done using sonication process: the tissue is heated with Focused

S. Bassis et al. (eds.), *Recent Advances of Neural Networks Models and Applications*,
Smart Innovation, Systems and Technologies 37, DOI: 10.1007/978-3-319-18164-6_19

UltraSound concentrating a high-energy beam on a specific point. This allows to reach a temperature higher than 50°C causing proteins coagulation and consequently inducing the fibroid tissue necrosis.

The planning, treatment and evaluation processes are possible thanks to MR Imaging (MRI) guidance, which can also be used to reconstruct maps of tissues temperature. This makes it particularly enabling for guiding and monitoring thermal therapies. Temperature monitoring is feasible with MRI thanks to temperature sensitivity to MR parameters such as Proton Resonance Frequency, T1 and T2 relaxation times, Proton Density, Magnetization Transfer and so on. In a MRgFUS treatment, a little area of the patient's organ is heated by a focused ultrasound beam, increasing temperature in that point. The process is repeated several times until the whole lesion area is treated. In Fig. 1 it is possible to see a sequence of temperature maps: the sonication burst takes about 30 second for each sonication, and the number of sonications are related to position, type, and size of uterus fibroid.

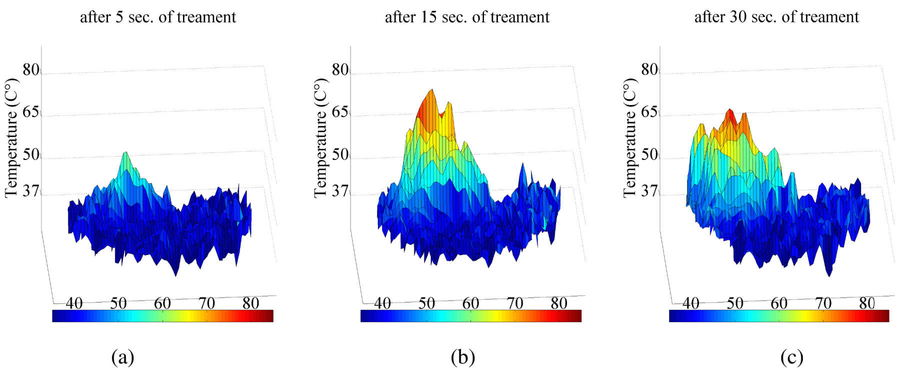


Fig. 1. (a) 3D plot of temperature map after 5 seconds treatment; the maximum temperature reached in the peak is about 52°C. (b) The temperature map after 15 seconds of sonication; (c) The temperature map after 30 seconds of sonication. The temperature peak is 87°C.

An interesting overview of MRI temperature methods is shown in [1]. Proton spectroscopic imaging, like PRF shift thermometry, uses phase mapping created from temperature-induced water proton chemical shift. MRI-derived temperature maps can be constructed using Gradient Recalled Echo (GRE) imaging sequences [5], by measuring the phase change resulting from the temperature-dependent change in resonance frequency. In order to eliminate temperature-independent artefacts such as magnetic field in-homogeneities, one or more baseline images are acquired before thermal therapy and subtracted from images during heating. The phase differences are proportional to temperature-dependent PRF shifts and the assessment of temperature rises ΔT is possible according to the following equation:

$$\Delta T = \frac{\varphi(T) - \varphi(T_o)}{\gamma \alpha B_o TE} \tag{1}$$

where $\varphi(T)$ is the phase map in the current temporal instant, $\varphi(T_0)$ is the baseline phase at a known temperature (i.e. 37°C), γ is the gyromagnetic ratio, $\alpha=-0.01 ppm/C°$ is the PRF change coefficient, B_0 is the strength of the magnetic field, and TE is the echo time of the MR acquisition protocol.

Motion of anatomical region undergone to the MRgFUS treatment is one of the most prevalent problems for temperature monitoring with PRF phase mapping. Intra-scan motion is caused by movement of an object during MR image acquisition, resulting in a poor quality image with typical blurring and ghosting artefacts. Inter-scan motion is due to motion or displacement of an object between the acquisitions of consecutive images. Methods for temperature estimation in presence of motion can be divided into two categories: (i) methods based on a multi-baseline strategy and (ii) methods based on a referenceless strategy.

Multi-baseline methods take background phase information before heating at various position of the organs during the respiratory and/or cardiac cycle. The selection of the corresponding baseline image is performed by determining the organ's position [9][10][11].

Referenceless methods estimate heating from a treatment image itself, without a baseline image used as temperature reference. Supposing that the phase image has a smooth tendency under the heated area, this kind of methods fit polynomial functions [3] or uses a weighted least-squares fit [4] to the surrounding phase. The extrapolation of the reconstructed piece of baseline image is useful for background phase estimation, which is then subtracted from the actual phase to evaluate the phase difference after the heating caused by ultrasound sonication.

Considering that in classical PRF shift thermometry there are obvious problems of artefacts, most prevalently due to motion, and in referenceless thermometry the accuracy of the interpolation lacks in precision, a novel interpolation method is applied to the issue of the referenceless thermometry. This method has been successfully tested [16] using MRgFUS ablation on a ex-vivo animal muscle and reconstructing temperature maps using RBF interpolation methods. In this paper method has been applied to real in-vivo treatments of uterine fibroids, evaluating the baseline phase maps with great results.

The paper is organized as follows: in Section 2 theoretical background on Radial Basis Function (RBF) is introduced; in Section 3 the proposed interpolation model is presented; Section 5 illustrates the obtained experimental results; finally, in Section 6, some conclusions are reported.

2 Radial Basis Functions

The idea of RBF Networks derives from the theory of function approximation. One of the most used approaches in literature to address the interpolation problem is to fit data using a polynomial function. However, an invertible system that defines the interpolator is not guaranteed for all the interpolation points, and often shows spurious bumps. The main features of RBF interpolators are:

- they are two-layer feed-forward neural networks;
- each hidden nodes implement a radial basis function;

- the network training finds the weights from the input to hidden layer and then the weights from the hidden to output layer are calculated;
- the geometry of the input points is not restricted to a regular grid;
- the networks are very good for interpolation purposes, in particular if there are large areas of missing data.

The interpolation of N data points requires that each of the D dimensional input vectors $x^p = \{x_i^p : i = 1,2,\dots,D\}$ is mapped onto the corresponding output target t^p, finding a function $f(x^p) = t^p$, $\forall p = 1,2,\dots,N$. The RBF function approach uses a set of basis functions that are combined linearly:

$$f(x) = \sum_{p=1}^{N} w_p \phi(\|x - x^p\|) \tag{2}$$

The idea is to find the weights w_p so the function fits through the data points:

$$f(x^q) = \sum_{p=1}^{N} w_p \phi(\|x^q - x^p\|) = t^p \tag{3}$$

The non-linear function $\phi(\cdot)$ is the interpolating radial basis function kernel. Some of the most commonly used basis functions are:

Table 1. Common kernels for radial basis functions

Radial Basis Function	Expression	Constrain
Linear	$\phi(r) = r$	
Multi-Quadric	$\phi(r) = (r^2 + \sigma^2)^{1/2}$	width $\sigma > 0$
Thin-Plate-Spline	$\phi(r) = r^2 \ln(r)$	
Gaussian	$\phi(r) = \exp\left(-\frac{r^2}{2\sigma^2}\right)$	width $\sigma > 0$

The RBF network is composed of two layers, and the N training patterns $\{x_i^p, t^p\}$ determine the weights directly. The hidden layer multiplies the activation units as shown in Fig. 2.

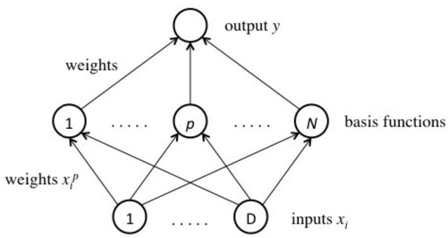


Fig. 2. The structure of a neural network implementing the RBFs as hidden layer

In this paper we are particularly concerned with 2D (depth-map) [12][13] data and we will consider Linear, Thin-Plate Spline and Multi-Quadratic interpolators.

The surveys of Powell and Light [14][15] are excellent references for the properties of radial basis functions. The σ value (in Multi-Quadric function) is responsible for the sensitivity of the interpolator. In the experiments, a very little value (of order 10^{-3}) is good for the interpolation purpose.

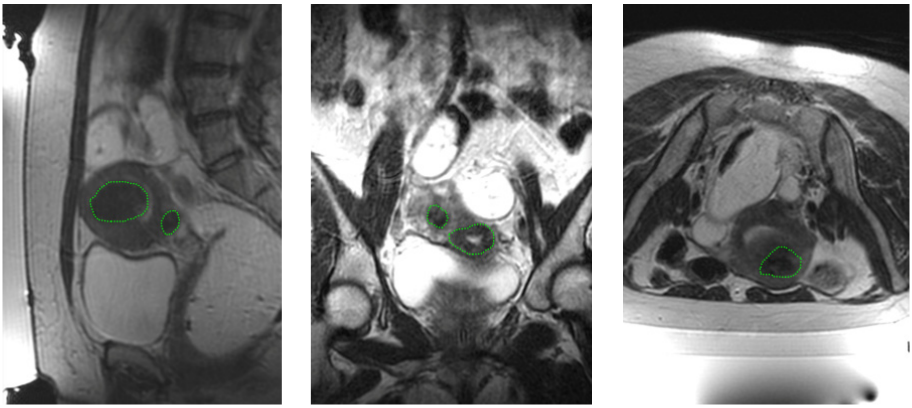
Moreover, often the data to interpolate are noisy. In presence of noise, one may consider to relax the exact interpolation requirement by means of regularization. This is possible by modifying the equation (2) as follows:

$$f(x) = \sum_{p=1}^{N} w_p \phi(\|x - x^p\|) + \lambda I \tag{4}$$

adding a relaxation parameter λ that controls the amount of smoothing of the interpolation, and I is the identity matrix. In the $\lambda=0$ case, the equation is reduced to exact interpolation; in case that the parameter is highly regularized, the TPS model degenerates to the least-squares affine model [18].

3 The Workflow of the Proposed Interpolation Method

The MRgFUS treatment uses ultrasound beams that hit the interested organ. In this paper we have evaluated temperature reconstructions of treatments regarding women affected by single/multiple uterine fibroid. In Fig. 3, an uterine fibroid has been highlighted before the thermal treatment.

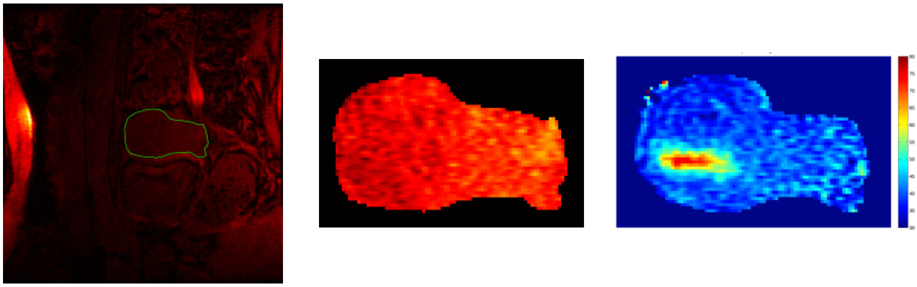


(a) (b) (c)

Fig. 3. An uterine fibroid in sagittal (a), coronal (b) and axial (c) view. The fibroid will be ablated with MRgFUS treatment

Referenceless thermometry estimates baseline phase from each acquired image phase and subtracts it from current image as in classical PRF thermometry [3].

In this work we have focused our attention to the effectiveness of the referenceless thermometry that uses a Polynomial for the interpolation [3], and we compared our proposed interpolation, that uses Radial Basis Functions, against the Polynomial one.



(a) (b) (c)

Fig. 4. (a) The area interested by the treatment; (b) Magnification of interested area; (c) Thermal map of the MRgFUS treatment. The blue area will be used for interpolation.

Here, our gold standard is the temperature extrapolated using classic PRF shift method [1]. As shown in Fig. 4, estimation is possible because in thermal therapy only a small region of the organ is affected by temperature change, and the phase outside the heated region can be used to determine the background phase.

For each temporal instant, the baseline phase below the heated area is evaluated interpolating the surrounding area using the Radial Basis Functions. The selection of a Region Of Interest (ROI) inside the treated organ (the female uterus in this case) makes possible to extract the heated area from the surrounding (not treated) area. The heated area that contains phase variations due to thermal treatments is removed, and the remaining area is used as input data to train the artificial neural network, as shown in Fig. 5. In correspondence of the sonication spot (Fig. 5a) the phase map shows a negative peak that represents a positive temperature variation (because the α coefficient is negative).

The proposed method (Fig. 6) for enhancing the referenceless thermometry by using RBF interpolation has been implemented as follows:

1. once the series of images is acquired, we recover the original phase from the 2π-wrapped phase images by using the Goldstein, Zebker and Werner's algorithm [6];
2. the RBF artificial neural network takes input data from the region between the sonicated area and the uterine contour;
3. the area to be reconstructed is iteratively interpolated by using RBF, which represents a practical solution for the problem of interpolating incomplete three-dimensional surfaces. The implementation of the reconstruction algorithm invokes iterative refinement to improve the accuracy of the solution;
4. for each temporal instant the extrapolated baseline phase that is used together with the global (currently heated) image.

This follows the PRF principles used for temperature rise assessment. The RBF network interpolates the masked area according to the specific radial basis functions: Linear (or Euclidean), Multi-Quadratic, Thin-Plate Spline, etc., solving it by using the double precision diagonal pivoting method from Lapack [17].

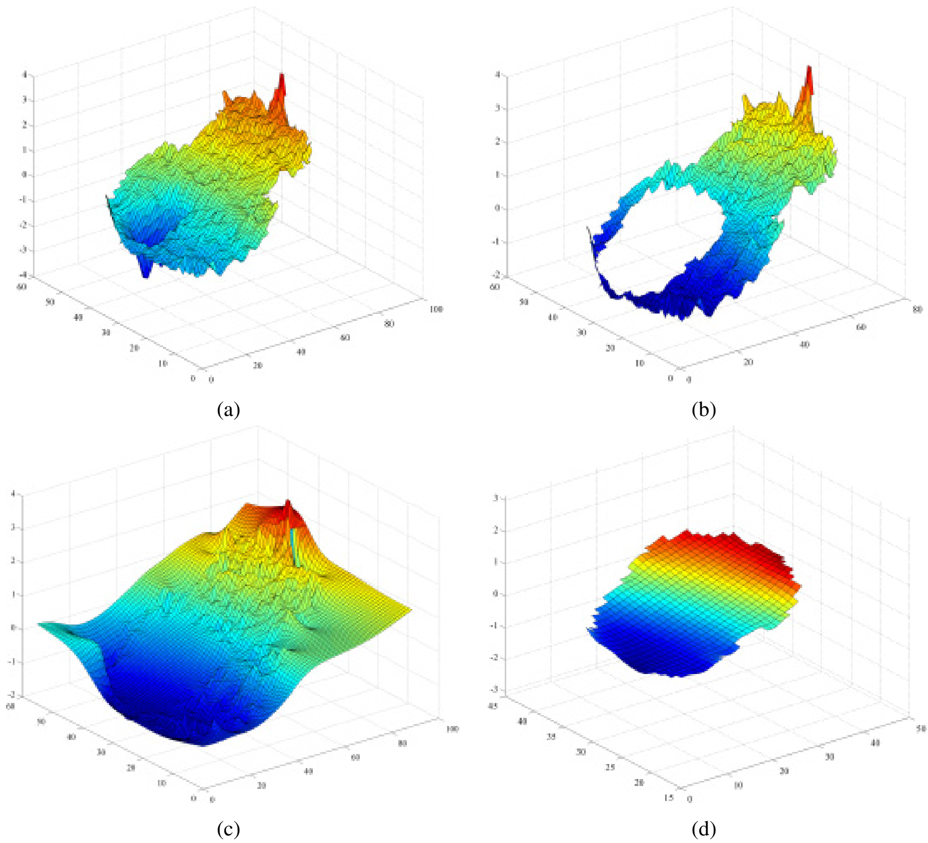


Fig. 5. (a) A 3D plot of the whole phase information of the organ: with a depression corresponding to the sonication shot (blue area); (b) the region affected by the sonication is removed, and the surrounding area is used to train the radial basis function network; (c) the reconstructed baseline obtained through the proposed interpolation algorithm (in this case it is used the Thin-Plate Spline kernel); (d) magnification of the interpolated area

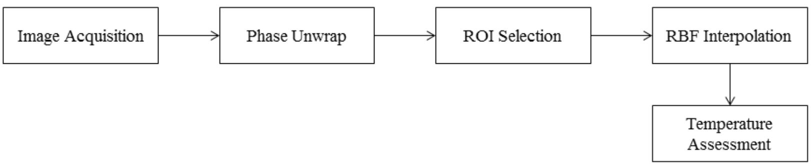


Fig. 6. The workflow of the proposed method

We found experimentally that the better interpolator for this particular kind of noisy data is the Linear RBF, but often during experimentation we found that also TPS and Multi-Quadratic have shown good results. The baseline phase is now reconstructed for each temporal instant and using it in conjunction of the phase image, according to PRF equation (1), we obtain the temperature rise of the whole sonication.

4 Experimental Results

Ten MR datasets related to ten female patients undergone to MRgFUS treatments for ablation of intra-uterine fibroid have been processed and evaluated. All the MR images are acquired by a GE Signa HDxt 1.5 Tesla scanner, and the ultrasound sonications are performed by an Insightec ExAblate 2100 system. Each hyperthermia sonication takes several seconds to focus high power ultrasounds in the chosen focal point. During each sonication the MR scanner records about 8-12 temporal instants, and each of them is composed of a tern of morphological-real-imaginary images. The real and imaginary parts are combined together to reconstruct phase maps. The evaluation of our approach was performed by calculating Root Mean Square (RMS) errors between the original baseline and each reconstructed (Polynomial and our Radial Basis Functions) interpolation, and calculating the differences (in C°) of the mean temperature value between the original PRF temperature and those provided by polynomial and our RBF approach. The kernels here used are the Euclidean, Thin-Plate Spline and the Multi-Quadratic one (Fig. 7).

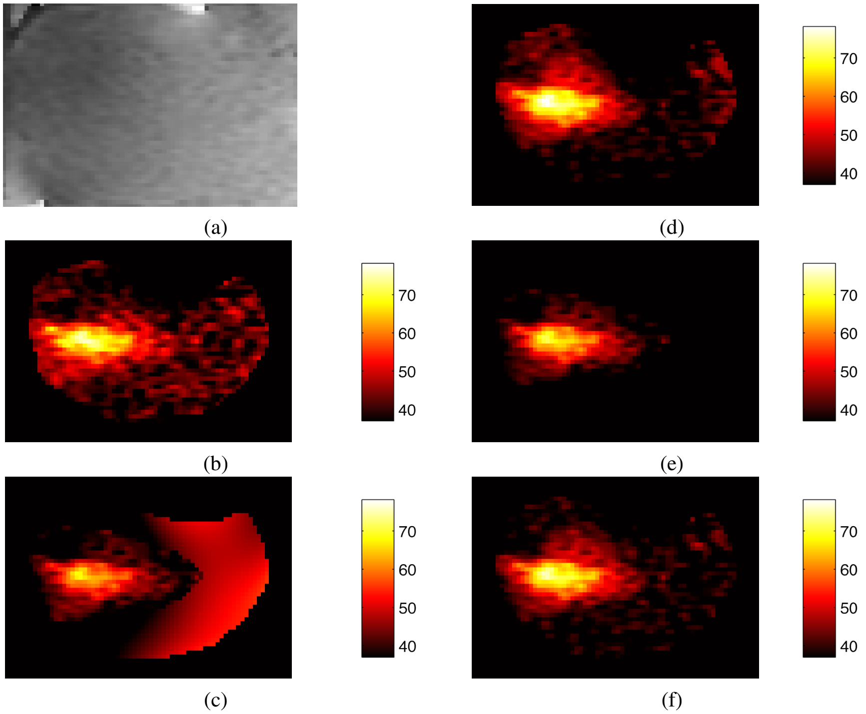
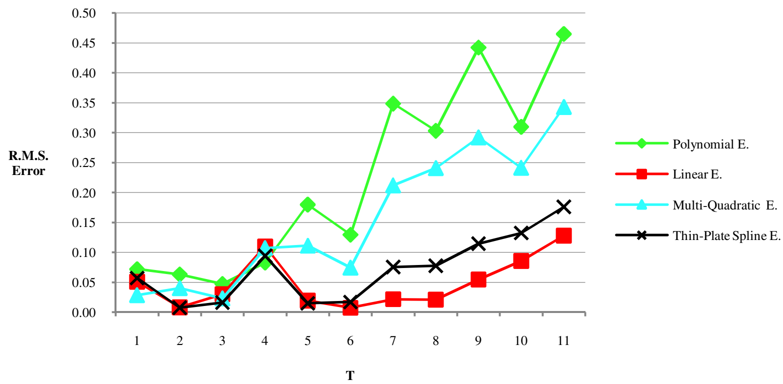
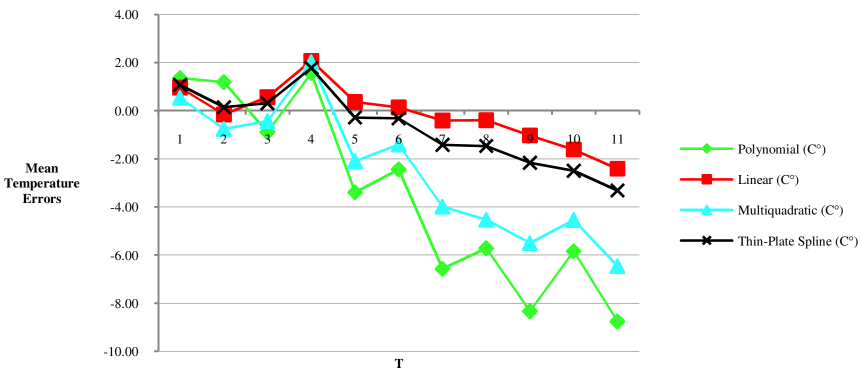


Fig. 7. Temperature reconstruction for a temporal instant during MRgFUS treatment: (a) the morphologic MR image; (b) temperature assessment using the classical PRF shift method; (c) temperature assessment using the Polynomial method; (d) temperature assessment using the Linear RBF method; (e) temperature assessment using the Multi-Quadratic RBF method; (f) temperature assessment using the Thin-Plate Spline RBF method. The depicted values are in °C.

The natural criterion for assess a reconstructed phase image is how closely it matches the baseline surface prior to the removal of the heated area. The interpolator fitted to the incomplete phase-map is then compared with the original baseline surface. Obtained temperature assessments in a MRgFUS treatment for the ablation of a uterine fibroid are shown in Fig. 8a. In this figure the RMS error shows that RBF reconstructions (Linear and Multi-Quadratic) has better results with respect to Polynomial reconstruction, assuming that the PRF temperature is the gold standard. Results show a huge increase of precision on the whole reconstructed area. These results are confirmed in Fig. 8b, where all the mean temperatures of the treated areas related to thermal treatments of all patients have been compared to PRF temperature.



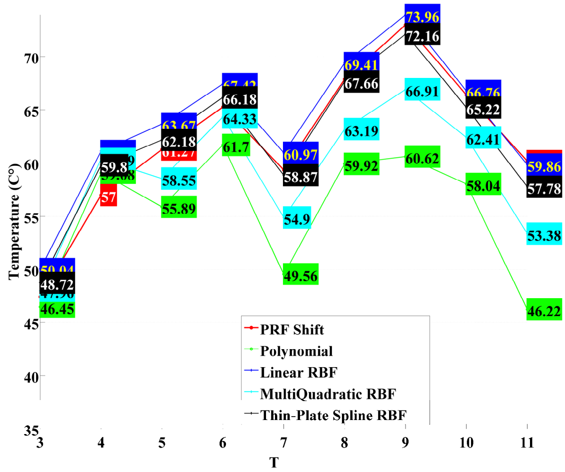
(a)



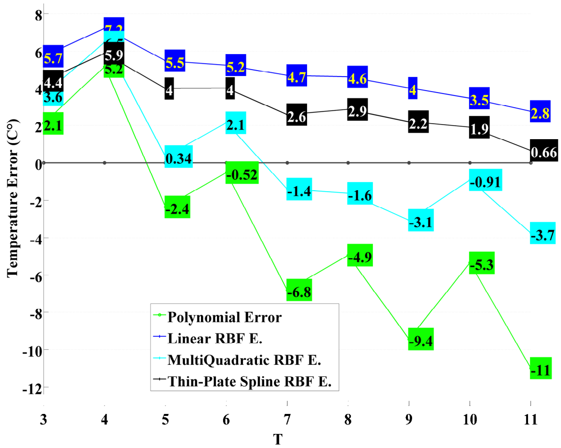
(b)

Fig. 8. (a) RMS errors for different kind of reconstruction methods compared to classical PRF Shift thermometry; (b) Mean temperature errors (°C) of the whole area hit by thermal treatment.

In Fig. 9a is depicted to see the temperatures evaluation in a random chosen point of the treatment area. All the RBF-based reconstructed temperatures (the blue, cyan, and black lines) runs very close to the gold standard PRF temperature (red line); we cannot say the same for the polynomial interpolation (green line). This demonstrates that radial basis functions are a very good kind of interpolator for this type of noisy data, even if there are large regions with missing data.



(a)



(b)

Fig. 9. Temperature behaviour in a point of the treatment area: (a) temperature rise (in °C) for a treatment of about 32 seconds. The red line is the reference *PRF* temperature, the green line is the *Polynomial* reconstructed temperature; the black *(Thin-Plate Spline)*, blue *(Linear)* and cyan *(Multi-Quadratic)* lines are the RBF-based reconstructed temperatures. (b) The variation (error) of reconstructed temperatures compared with the *PRF* temperature.

Fig. 9b confirms the goodness of the RBF reconstruction: for example, in the ninth temporal instant, the PRF temperature is 73.04°C. The RBFs temperatures differs of 3-4°C, while the Polynomial temperature is about 10°C. less. In a MRgFUS treatment, this can lead to continue the sonication process even if it is not necessary, surely causing pain to the patient and possible damages in surrounding tissues. In conclusion, the RBF reconstruction method gains all the advantages of referenceless thermometry avoiding lacks of precision of the Polynomial interpolation temperature reconstruction.

5 Conclusion

RBF neural networks are a good and flexible tools that allow for the reconstruction of unknown data. The effectiveness of the proposed approach has been demonstrated using 10 MR dataset of 10 female patients undergone to uterine fibroids ablation MRgFUS treatments. Polynomial reconstruction can over/under estimate the temperatures: this can lead to break the sonication before reaching the temperature established. The risk is the missing proteins denaturation, pain inducted in patients, and damage to surrounding tissues. RMS errors and temperature differences show a huge increase of precision in comparison with other kind of interpolators.

Future works will investigate the real precision of the PRF method, by measuring real temperature rises in MRgFUS treatments using thermocouples or optical fibres inserted in a phantom and acquiring the phase variations induced by the heating process. Since the reconstruction method is heavily dependent from ROIs selection, we are also investigating automatic methods for organ and sonication spot segmentation[8]. The integration of this RBF-based interpolation method with automatic segmentation approaches could reduce the operator-dependence of the algorithm and, consequently, the final error in the temperature reconstruction.

References

1. Rieke, V., Butts, K.: MR Thermometry. Journal of Magnetic Resonance Imaging 27, 376–390 (2008)
2. Kim, J.H., Hahn, E.W.: Clinical and biological studies of localized hyperthermia. Cancer Res. 39, 2258–2261 (1979)
3. Rieke, V., Vigen, K.K., Sommer, G., Daniel, B.L., Pauly, J.M., Butts, K.: Referenceless PRF shift thermometry. Magn. Reson. Med. 51, 1223–1231 (2004)
4. Kuroda, K., Kokuryo, D., Kumamoto, E., Suzuki, K., Matsuoka, Y., Keserci, B.: Optimization of self-reference thermometry using complex field estimation. Magn. Reson. Med. 56, 835–843 (2006)
5. Ishihara, Y., Calderon, A., Watanabe, H., Okamoto, K., Suzuki, Y., Kuroda, K., Suzuki, Y.: A precise and fast temperature mapping using water proton chemical shift. Magn. Reson. Med. 34, 814–823 (1995)
6. Goldstein, R.M., Zebker, H.A., Werner, C.L.: Satellite radar interferometry: two-dimensional phase unwrapping. Radio Sci. 23, 713–720 (1988)

7. Hurwitz, M., Machtinger, R., Fennessy, F.: Magnetic resonance-guided focused ultrasound surgery for treatment of painful osseous metastases. In: Progress in Biomedical Optics and Imaging - Proceedings of SPIE, vol. 7901, art. no. 79010M (2011)
8. Militello, C., Vitabile, S., Russo, G., Candiano, G., Gagliardo, C., Midiri, M., Gilardi, M.C.: A semi-automatic multi-seed region-growing approach for uterine fibroids segmentation in MRgFUS treatment. In: Proceedings of 7th International Conference on Complex, Intelligent, and Software Intensive Systems, pp. 176–182 (2013), doi:10.1109/CISIS.2013.36
9. Vigen, K.K., Daniel, B.L., Pauly, J.M., Butts, K.: Triggered, navigated, multi-baseline method for proton resonance frequency temperature mapping with respiratory motion. Magn. Reson. Med. 50, 1003–1010 (2003)
10. Shmatukha, A.V., Bakker, C.J.G.: Correction of proton resonance frequency shift temperature maps for magnetic field disturbances caused by breathing. Phys. Med. Biol. 51, 4689–4705 (2006)
11. Roujol, S., Ries, M., Quesson, B., Moonen, C., de Senneville, B.D.: Real-time MR-thermometry and dosimetry for interventional guidance on abdominal organs. Magn. Reson. Med. 63, 1080–1087 (2010)
12. Beatson, R., Newsam, G.: Fast evaluation of radial basis functions: I. Comput. and Math. with Applicat. 24(12), 7–19 (1992)
13. Carr, J.C., Fright, W.R., Beatson, R.K.: Surface Interpolation with Radial Basis Functions for Medical Imaging. IEEE Transactions on Medical Imaging 16(1) (February 1997)
14. Powell, M.J.D.: The theory of radial basis function approximation in 1990. In: Light, W.A. (ed.) Advances in Numerical Analysis II: Wavelets, Subdivision Algorithms and Radial Functions, pp. 105–210. Oxford Univ. Press, Oxford (1992)
15. Light, W.A.: Some aspects of radial basis function approximation. In: Singh, S.P. (ed.) Approximation Theory, Spline Functions and Applications, pp. 163–190. Kluwer, Dortrecht (1992)
16. Agnello, L., Militello, C., Gagliardo, C., Vitabile, S.: Referenceless Thermometry using Radial Basis Function Interpolation. In: World Symposium on Computer Applications & Research, WSCAR (2014), doi:10.1109/WSCAR.2014.6916834
17. Lapack Users Guide, Society for Industrial and Applied Mathematics, Philadelphia, PA (1992)
18. Belongie, S., Malik, J., Puzicha, J.: Shape Matching and Object Recognition Using Shape Contexts. IEEE Transactions on Pattern Analysis and Machine Intelligence 24(4), 509–522 (2002)