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Accelerated electron paramagnetic resonance imaging using partial Fourier compressed sensing reconstruction

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Abstract

Purpose—Electron paramagnetic resonance (EPR) imaging has evolved as a promising tool to provide non-invasive assessment of tissue oxygenation levels. Due to the extremely short T_2 relaxation time of electrons, single point imaging (SPI) is used in EPRI, limiting achievable spatial and temporal resolution. This presents a problem when attempting to measure changes in hypoxic state. In order to capture oxygen variation in hypoxic tissues and localize cycling hypoxia regions, an accelerated EPRI imaging method with minimal loss of information is needed.

Methods—We present an image acceleration technique, partial Fourier compressed sensing (PFCS), that combines compressed sensing (CS) and partial Fourier reconstruction. PFCS augments the original CS equation using conjugate symmetry information for missing measurements. To further improve image quality in order to reconstruct low-resolution EPRI images, a projection onto convex sets (POCS)-based phase map and a spherical-sampling mask are used in the reconstruction process. The PFCS technique was used in phantoms and *in vivo* SCC7 tumor mice to evaluate image quality and accuracy in estimating O_2 concentration.

Results—In both phantom and *in vivo* experiments, PFCS demonstrated the ability to reconstruct images more accurately with at least a 4-fold acceleration compared to traditional CS. Meanwhile, PFCS is able to better preserve the distinct spatial pattern in a phantom with a spatial resolution of 0.6 mm. On phantoms containing Oxo63 solution with different oxygen concentrations, PFCS reconstructed linewidth maps that were discriminative of different O_2 concentrations. Moreover, PFCS reconstruction of partially sampled data provided a better discrimination of hypoxic and oxygenated regions in a leg tumor compared to traditional CS reconstructed images.

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Conclusions—EPR images with an acceleration factor of four are feasible using PFCS with reasonable assessment of tissue oxygenation. The technique can greatly enhance EPR applications and improve our understanding cycling hypoxia. Moreover this technique can be easily extended to various MRI applications.

Keywords

Electron paramagnetic resonance imaging; Compressed sensing; Single point imaging; Cycling hypoxia; Virtual coils

1. Introduction

1.1. Tumor hypoxia

Oxygen deprived (hypoxic) tumors are resistant to radiation therapy and chemotherapy [1–7]. Knowledge of the spatial distribution of the extent of hypoxia can optimize therapeutic strategies, such as targeting doses of radiation and/or the appropriately selecting hypoxic cytotoxins [8–11]. While certain tumors exhibit chronic hypoxia, hypoxic conditions can be intermittent or “cycling.” Cycling hypoxia has been shown to induce the expression of hypoxia-inducible transcription factor-1 α (HIF-1 α) and confer tumor cells and tumor vascular endothelial cells with enhanced pro-survival pathways, thus making tumors less responsive to therapy. The frequency of cycling hypoxia has been studied recently with a variety of techniques [12]. The literature suggests that hypoxic cycling ranges from minutes to hours or even days [13]. It is generally understood that the faster the frequency of cycling, the more likely the tumor is aggressive and has the tendency to be metastatic [14]. Thus, there is an urgent need for a technique that can facilitate the measurement of tumor hypoxia non-invasively at high temporal resolution to detect fluctuations in intratumoral oxygenation. Preferably, this should be done with high spatial resolution to accurately depict the margins of hypoxic regions within a tumor.

1.2. Electron paramagnetic resonance imaging (EPRI)

Electron paramagnetic resonance imaging (EPRI) has emerged as a promising technique to measure tumor hypoxia. EPRI is similar to MRI except that images are reconstructed from signals emanating from paramagnetic species that have unpaired electrons rather than protons. However, image acquisition using EPRI continues to be a challenge because of the extremely short relaxation time (on the order of microseconds) of electrons. Therefore a single point imaging (SPI) method has been adopted in EPRI, where a single free induction decay (FID) is sampled at each single k-space point following each excitation [15–17]. In SPI, spatial encoding gradients remain static after each RF excitation during data acquisition. K-space is sampled by stepping the encoding gradients one by one through the Cartesian space after a certain dead time (~ 350 ns). In SPI, it is possible to sample signals over an extended time range and acquire a series of images along the FID at each Cartesian point and gather information on T_2 -relaxation. Therefore, through the use of paramagnetic spin probes whose linewidth is proportional to pO_2 (such as Oxo63), the oxygen distribution maps can be extracted using the T_2 -decay information [18].

However, given the nature of SP-EPRI, an optimum balance must be achieved between temporal resolution and spatial resolution in order to effectively capture cycling hypoxia information. Currently, this compromise results in lowered temporal resolution (>5mins) needed to obtain images with reasonable spatial resolution. This factor limits the ability of EPRI to capture dynamic changes in biological phenomena as in the case with cycling hypoxia. Novel imaging methods that lead to shortened imaging times without losing spatial resolution are of crucial to extend the capability of EPRI.

1.3. State of art of imaging for cycling hypoxia

Because EPRI and MRI share the same image acquisition principles, many data acceleration techniques that have been developed for MRI can be applied in EPRI. Partial k-space acquisition (PAR) technique has been explored to reduce the image acquisition time in EPRI. In PAR, the acquisition time can be reduced by nearly half (46%) when combined with an elliptical sampling scheme without significantly sacrificing spatial resolution and with minimal loss in signal-to-noise ratio. Compressed sensing (CS) has also been adopted in dynamic EPRI. Jang et al. developed a new bilateral k-space extrapolation technique in combination with CS to enhance spatial and/or temporal resolution in SPI-EPRI [18]. They demonstrated that a T_2^* map with reasonable spatial and temporal resolution can be reconstructed using 12.5%–50% of the original k-space data for large encoding steps (61×61 for 8-fold, $95 \times 95 \times 95$ for 15-fold, $127 \times 127 \times 127$ for 30-fold acceleration). However, much remains to be explored regarding data acquisition reconstruction techniques in order to exploit the advantages of EPRI to probe important biological phenomena.

In this paper, we present our development of an improved technique that combines the advantages of partial Fourier transform and CS to arrive at a new image reconstruction algorithm – partial Fourier compressed sensing (PFCS). In PFCS, an augmented cost function which allows more accurate image estimation is reached by virtual measurements, which is derived from conjugate symmetry of k-space. Further, an improved spherical sampling pattern was developed to better secure the image contrast, especially for EPR images with low spatial resolution. Projection onto convex sets (POCS) [20–21] reconstructed image from the under-sampled k-space is used for the phase map estimation which is needed in partial Fourier transform. The performance of PFCS reconstruction was validated using phantoms and an *in vivo* mouse model of tumor hypoxia.

2. Theory

2.1. Partial Fourier transform

Partial Fourier transform can be formulized through the virtual coil concept which was first introduced by Blaimer et al. in 2009 [22]. In this technique, the hermiticity of k-space is applied to improve the reconstruction quality by finding an optimal estimation for the image that satisfies both the real measurements and its conjugate [22]. That is, finding an optimal image I such that

$$\left\| \begin{bmatrix} y \\ y^* \end{bmatrix} - H \cdot FT \cdot \left(\begin{bmatrix} P \\ P^* \end{bmatrix} \cdot I \right) \right\|^2 \quad (1)$$

is minimum. Here I is the real valued optimal image. H is the partial-sampling operator which samples slightly more than half of the k -space. y denotes the actual measurements. y^* is the corresponding conjugate points of y . p is the phase map of the image I . p^* is the conjugate of p . $\|\cdot\|$ represents l_2 -norm.

Theoretically, the image should be in real value. Thus the phase map p should be equal to an all-1 matrix and yield a perfectly reconstructed image. However, the actual value of each voxel in the image is complex due to background interference and magnetic field inhomogeneity. In this case the lower half of (1) can be viewed as the measurements from a set of virtual coils which can provide additional information regarding the image. Knowledge of this information can potentially lead to a more precise estimation of the image. The advantage of this framework is that partial Fourier reconstruction can be formulated as a typical linear system which can easily incorporate a regularization term, such as total variation or wavelet transform.

2.2. Compressed sensing

CS reconstructs images from significantly fewer measurements than traditional sampling methods with the exploitation of the signal sparsity, based on the fact that the majority of the information is contained in only a fraction of the entire data. The object function can be briefly described as follows: Let Ψ denote the linear operator that transforms from pixel Cartesian representation into sparse representation. M is the incoherent sparse-sampling operator. $\|\cdot\|_1$ represents l_1 -norm.

The object function of compressed sensing can be written as:

$$\min_I (\lambda \cdot \|\Psi(I)\|_1 + \|y - M \cdot FT \cdot (p \cdot I)\|^2) \quad (2)$$

In this optimization problem, $\|\Psi(I)\|_1$ guarantees the image sparsity, and $\|y - M \cdot FT \cdot (p \cdot I)\|^2$ promotes the data fidelity [23]. For medical imaging such as MRI, the image is naturally compressible by the sparsity of the image itself or in an appropriate linear transformable domain (total variance, wavelet, etc). Thus the application of CS can significantly accelerate the imaging process.

2.3. Partial Fourier compressed sensing (PFCS)

In the proposed PFCS technique, the advantages of virtual coils and CS are combined for better image quality. The Hermitian symmetry of k -space is utilized by augmenting the original system equations by replicating missing signals using the conjugate symmetry principle. Total variance is used as the sparsity component of the reconstructed image. Thus,

the new object function, after combining Eqs. (1) and (2) and replacing the sparsity term with total variance, can be formulated as follows:

$$\underset{I}{\text{minimize}} \left(\lambda \cdot \text{TV}(I) + \left\| \begin{bmatrix} y \\ y^* \end{bmatrix} - M * \text{FT} \cdot \left(\begin{bmatrix} p \\ p^* \end{bmatrix} \cdot I \right) \right\|^2 \right) \quad (3)$$

where TV stands for total variance operator.

An incoherent random sampling in k-space is necessary to diffuse noise from coherent aliasing caused by down-sampling. Also, the relatively small matrix size and low resolution typically used in preclinical EPRI necessitates the need to acquire more points near the center of the k-space to better secure the image intensities. For this purpose, we used a spherical-sampling mask to effectively sample k-space as part of the under-sampled acquisition. The sampling of k-space consists of two parts: (1) a fully sampled central region at a specified radius, and (2) a sparsely sampled peripheral region as shown in Fig. 1. The central partition covers half of the k-space points and the remaining half are sparsely sampled over the peripheral region avoiding conjugate symmetry equivalents. For example, in a $10 \times 10 \times 10$ grid of k-space (containing 1000 points), 250 points are sampled at an acceleration factor of 4. Among them, 125 points are included in central region and another 125 points are spread over the remaining peripheral k-space at approximately uniform spatial distribution. Various configurations of this sampling pattern were used to assess the performance of PFCS and CS reconstruction respectively.

We used the POCS reconstruction technique [21] to estimate p , the phase map for PFCS (see Eq. (3)). POCS operates by iteratively applying phase correction on an estimated image to prevent phase errors from exaggeration. In each iteration, the estimated k-space must match the acquired measurements with the limitation that the image phase is constrained to be that of the low resolution image, that is, the phase information from the center partition of the k-space as shown in the flow chart in Fig. 2. In the first loop as shown in the flow chart, the estimated image magnitude is from that of the under-sampled image $m_i(x,y)$. The phase constraint, which is the phase of the low resolution image $m_s(x,y)$, is applied to produce the new estimated image $m_n(x,y)$ by

$$m_n(x,y) = |m_i(x,y)| \cdot \exp(\arg(m_s(x,y))) \quad (4)$$

The corresponding Fourier data, $M_n(x,y)$, is computed by

$$M_n(x,y) = \text{FT}(m_n(x,y)) \quad (5)$$

where FT is the Fourier transform operator. Finally, the entries corresponding to the uncollected data in $M_n(x,y)$ are propagated to $M_{i+1}(x,y)$. In each iteration, the phase of the

new estimated image is constrained to be that of $m_s(x,y)$ to prevent increased phase errors. The loop continues until the image phase of $m_i(x,y)$ converges (~ 100 iterations). This converged image phase serves as the phase map estimation for PFCS.

Fig. 3 shows the phase map of fully acquired resolution phantom image and POCS estimation from one representative under-sampled datum. The phase differences within the imaging object are also displayed. Although some resolution details are lost since POCS restricts the estimation errors by applying low resolution phase correction in every iteration, the overall estimation error is quite small (<0.3 rad) within the object and warrants good PFCS reconstruction.

3. Experiments and methods

3.1. Equipment

The details of the EPRI system are found in previous publications [15,17,24]. Briefly, the home built spectrometer operates at 300 MHz. A parallel coil which achieved a Q in the range of 20–25 was used for the imaging experiments. The Trityl-based probe Oxo63 (GE Healthcare, Waukesha, WI) was used as the spin probe. The data were acquired by stepping the spatial encoding gradients from one point to the next in k-space. Each FID was sampled at 581 delay points at a rate of 5 ns after RF recovery dead time of about 350 ns, TR = 6 or 8 μ s, RF pulse width = 80 ns.

3.2. Phantom experiments

A resolution phantom and an oxygen phantom containing three vials with different concentrations of oxygen were used to test the spatial resolution and oxygen concentration differentiation of the reconstructed images. The resolution phantom was made of a Lucite cylinder with rectangular partitions with minimum slot width of 300 μ m filled with 3 mM Oxo63 solution (Fig. 4(a)). We acquired data on this phantom using two orthogonal phase encoding gradients ramping in 61 equal steps yielding a 2D 61×61 k-space matrix. The gradient maximum is 40 mT/m. Four thousand averages for each phase encoding point were acquired.

The second phantom had three vials containing 3 mM Oxo63 which were saturated with 0, 2, and 5% oxygen respectively (Fig. 4(b–c)). 3D EPRI images were obtained with a 2.5 cm diameter resonator. Data were encoded using three orthogonal phase encoding gradients ramping in 21 equal steps yielding a $21 \times 21 \times 21$ k-space matrix. The three different gradient maximums for multi-gradients were set to 9.6/11.4/14 mT/m respectively. Three consecutive data sets each with 10,000 averages for each phase encoding point were fully acquired. T_2^* and linewidth maps were calculated (see below) from 21 images with delay time ranging from 850 ns to 1375 ns at uniform time intervals, following image reconstruction using the CS and PFCS techniques respectively.

3.3. In vivo data

Female C3H mice were used for tumor EPR imaging (Fig. 4(d–f)). The animals were received at 6 weeks of age and housed five per cage in a climate controlled room with food

and water supply. SCC7 tumor cells were implanted on the right hind leg and grown to 1.5 cm in diameter (~2 weeks, Fig. 4(d)). Body weights of the mice were approximately 25 g. The mice were anesthetized by isoflurane inhalation (4% for induction and 1.5% for maintaining anesthesia) and remained still with the tumor leg placed inside a 1.7 cm resonator (Fig. 4(f)). During the experiment, the mice were subjected to an alternating breathing cycle of 10 min air→10 min carbogen (95% O₂ plus 5% CO₂)→10 min air to induce oxygen change inside the tumor. Oxo63 was injected as a 1.125 mmol/kg bolus into its tail vein followed by 0.04 mmol/kg/min continuous injection [25]. Nine consecutive images with 19 × 19 × 19 phase encoding steps along with 9/11.25/13.5 mT/m multigradients were acquired within one breathing cycle. The repetition time was 6 μs. One thousand averages for each encoding step were acquired. The scan time for each multi gradient full acquisition was roughly 3.5 min. Data were then down-sampled by spherical sampling with an acceleration ratio of 4 (25% k-space, 1714 points). The size of the center region was 857 points (12.5% k-space). Fifteen images with delay time ranging from 600 ns to 1050 ns with identical time intervals were reconstructed using the CS and PFCS technique respectively.

3.4. Data analysis and linewidth estimation

The fully acquired data from each experiment was down-sampled with the spherical sampling mask to mimic an acceleration factor of 4 (25% k-space). The performance of each reconstruction method was quantified using normalized mean square error (nMSE) which is calculated by:

$$\text{nMSE} = \sqrt{\frac{\|x - \hat{x}\|^2}{\|x\|^2}}$$

Where x and $\hat{x}$ represent fully and reconstructed images respectively. The difference maps between the reconstructed and fully acquired images were calculated to further facilitate the comparison.

In SP-EPR imaging, the imaging FOV decreases as delay time increases for each corresponding point in the FID. In other words, the resolution of the images increases albeit with reduced signal to noise ratio due to reduced FOV and T_2 decay. In order to obtain images with identical FOV, we adopted the method of reference scaling factor [26]. In this method, the k-spaces corresponding to the different images with different FOVs were padded with zeros based on the scaling factor with respect to the reference FOV (usually the smallest FOV). The images were then truncated into the size of the desired FOV resulting in a series of images with identical FOV. This allowed us to compute T_2^* on a pixel-by-pixel basis using linear least-square curve fitting to the log-linearized image magnitude which is formulated as:

$$\ln(I(k)) = -\frac{1}{T_2^*} \cdot t + \ln(I_0(k)) \quad (6)$$

where $I(k)$ denotes intensity of k th pixel at time t , and I_0 denotes the pixel intensity at $t = 0$. The linewidth is inversely proportional to T_2^* and is calculated by: [27]

$$\text{linewidth} = \frac{1}{\pi T_2^*} \quad (7)$$

Moreover, multi-gradient acquisition was used to avoid ringing artifacts [26].

4. Results

The results of the resolution phantom are shown in Fig. 5. The PFCS reconstructed image showed better image fidelity than traditional CS. Furthermore, the blurring caused by the under-sampling was less, and the outline of the object was better preserved.

The images and linewidth maps of one representative oxygen phantom data reconstructed by CS and PFCS are shown in Fig. 6. As the figures demonstrate, PFCS images provided a better reconstructed image showing better details especially at the center of each tube (red arrow). PFCS also achieved a lower nMSE (0.0389) than CS (0.0703). The linewidths of the oxygen phantoms fell in the range of 20–35 μT (200–350 mG), which agreed with the expected linewidth for 0–5% pO_2 [26].

Fig. 7 shows representative *in vivo* image and linewidth maps reconstructed from CS and PFCS respectively. Differences of images and linewidths are also displayed for the purpose of comparison. PFCS displayed less error (0.0502) compared to the fully acquired images than the CS (0.0448) reconstruction especially on the tumor tissue which is shown by the red arrow in difference maps. The green arrow on the linewidth maps indicates a small hypoxic band across the center of the tumor. In the PFCS linewidth map, the artifacts caused by the down-sampling were reduced compared to the conventional CS. This is evident by the outline of the band was retained and distinguishable using the PFCS reconstructed linewidth maps. Using CS reconstruction however, these bands were significantly blurred and in some cases indistinguishable. The improvement made by PFCS was also shown by lower nMSE (0.0613 vs 0.0625).

Fig. 8 shows six representative fully acquired and PFCS reconstructed images in one alternating breathing cycle (air→carbogen→air) in the mouse tumor. The linewidth maps produced by fully sampled images and PFCS reconstructed images are shown in Fig. 8(b) and (c) respectively. The linewidth variation curves of two specific regions, denoted as area 1 and area 2 in (a), are depicted in Fig. 8(d). Area 1 is the region with a fluctuated oxygen level, while Region area 2 is relatively stable. The diamonds and circles represent the linewidth variation from regions area 1 and area 2 respectively. For area 1, the curve

demonstrated an increase in oxygen level while the mouse is breathing carbogen. After the breathing cycle, the oxygenation returned to its original state. For area 2, the linewidth curve slightly increased during carbogen inhalation, and then slowly decreased after the air was supplied. The fluctuation of the linewidth curves in both areas was captured by PFCS reconstructed linewidth maps.

5. Discussion

We demonstrated that PFCS provides a better image reconstruction than CS on both phantom and *in vivo* data. We also demonstrated the oxygen variation induced by carbogen inhalation can be captured by PFCS estimated linewidths. Regions with fluctuating and stable oxygen levels were distinguishable using the PFCS technique. In addition, the noise associated with aliasing is better suppressed using the PFCS reconstruction compared to the CS technique.

The proposed PFCS reconstruction method provides significant improvement in the temporal resolution achievable using SP-EPRI. For example, for a raw data matrix with $19 \times 19 \times 19$ encoding step EPRI, the total scan time is approximately 3.5 min. With PFCS, one could achieve the same with a scan time < 1 min with minimal loss of information. This translates into enhanced spatial-temporal resolution critical to the studies of transient biological events.

Due to a smaller matrix size in SP-EPRI acquisition, the image information is usually more widely distributed within the whole k-space than conventional MRI. With the proposed spherical-sampling, the center of k-space is better covered than conventional cube sampling pattern used in CS MRI due to a larger size of the center region (12.5% vs 4–6% of k-space for fully acquired center region). This however causes the loss of the resolution information in the image, which is now more sparsely sampled. Nevertheless, this insufficiency is compensated in PFCS by the virtual measurements given by the conjugate symmetry of k-space.

PFCS requires phase map estimation from under-sampled k-space. POCS reconstructed image is suitable to serve as the phase map estimation since it prevents estimation errors from exaggeration by continuously applying phase constraint derived from low-resolution images. One concern is that the estimated phase map would be smoother and may lose the detailed variation existing in the true phase map. From our observation, the phase within the imaging object is usually stable and smooth in EPRI. Benefitting from this phase consistency, POCS estimated phase maps can provide reasonable PFCS image reconstruction.

6. Conclusion

In this paper, we proposed a new method, PFCS, for SP-EPRI which can provide significant acceleration with minimum loss in spatial and temporal resolution compared to a fully sampled image. PFCS fully exploits the conjugate symmetry and sparsity of k-space and is capable of reconstructing images from merely 25% of the k-space. The spherical sampling and POCS phase map estimation are used to facilitate the reconstruction.

The PFCS derived linewidth maps which are important for assessment of oxygen concentration appear to provide reliable pO₂ information compared to a fully sampled technique. These results indicate that pO₂ measurements are possible using accelerated EPRI to measure even higher rates of cycling hypoxia.

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Fig. 1.

Spherical sampling mask. The spherical sampling mask is divided into (1) the center with full acquisition, and (2) peripheral with randomly sparse sampling. In this trajectory, the center is a sphere with half the amount of applicable k-space points. In this example ($ac = 4$), the size of the center contains 12.5% of k-space.

Fig. 2.

The POCS algorithm implemented in PFCS on spherical-sampling masks. The new estimated image, $m_n(x,y)$, is obtained from the multiplication of the magnitude of image $m_i(x,y)$ from undersampled k-space and the phase constraint derived from the image of symmetric center data $m_s(x,y)$. The missing points in the original under-sampled k-space $M_i(x,y)$ are filled with the corresponding points from the new estimated k-space $M_n(x,y)$ and start a new iteration. After 100 iterations, the phase map of the output image $m_{i-last}(x,y)$ will serve as the phase map estimation for PFCS.

Fig. 3.

Phase maps of the fully acquired, POCS reconstructed resolution phantom image, and the differences between the two. Please note that the differences between the full acquisition and the POCS phase map estimation within the imaging object are quite small compared to background.

Fig. 4.

Experiment setup of the phantoms, resonator, *in vivo* tumor and the relative position of the animal used. The resolution phantom is displayed in (a). The vial phantom comprised of three vials containing 3 mM Oxo63, which were saturated with 0, 2, and 5% oxygen is shown in (b) (c). SCC7 tumor cells were implanted into right hind leg of the mouse (d). The mouse was fixed in a 1.7 cm resonator (e) (f) and subjected to an alternating breathing cycle of 10 min air → 10 min carbogen → 10 min air during the imaging process. Oxo63 was continuously injected during the acquisition.

Fig. 5.

The results of image reconstruction on the resolution phantom using 4-fold acceleration. The first column is the fully acquired image of the resolution phantom. The second and the third columns are the images reconstructed by CS and PFCS, respectively. The difference maps (CS Diff and PFCS Diff) between the two reconstructed images and the fully acquired image are also displayed for comparison. The PFCS reconstructed image retained most of the details of the resolution phantom. The improvement can also be seen in the difference map as well as the lower nMSE.

Fig. 6.

The images and linewidth maps of one representative tube phantom datum using 4-fold acceleration. PFCS images provided less error especially at the center of each tube (shown in red arrow), as also reflected by lower nMSE. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 7.

The images and line widths reconstructed by CS and PFCS for *in vivo* data using 4-fold acceleration. The differences are also shown in the figure. PFCS provided a more accurate estimation at the center of tumor tissue (red arrow). The detailed structure in linewidths is also better retained by PFCS (green arrow). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig.8.

Linewidth maps and pO_2 curve within the tumor tissue in one alternating breathing cycle of 10 min air $\rightarrow$ 10 min carbogen (95% O_2 plus 5% CO_2) $\rightarrow$ 10 min air to induce oxygen change inside the tumor. The anatomical information is shown in the MRI image (a). The linewidth maps from fully acquired and PFCS reconstructed images are displayed in (b) and (c) respectively. The red contour indicates the position of linewidth maps shown in (b) and (c). The linewidth variation curve along the time of the two areas depicted in (a) is shown in (d). Area 1 corresponds to the region with fluctuating oxygen level, while area 2 is the region with stable oxygenation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)