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Accelerating $T_{1\rho}$ Cartilage Imaging Using Compressed Sensing with Iterative Locally Adapted Support Detection and JSENSE

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Abstract

Purpose—To accelerate $T_{1\rho}$ quantification in cartilage imaging using combined compressed sensing with iterative locally adaptive support detection and JSENSE.

Methods—To reconstruct $T_{1\rho}$ images from accelerated acquisition at different time of spin-lock (TSLs), we propose an approach to combine an advanced compressed sensing (CS) based reconstruction technique, LAISD (Locally-Adaptive Iterative Support Detection), and an advanced parallel imaging technique, JSENSE. Specifically, the reconstruction process alternates iteratively among local support detection in the domain of principal component analysis, compressed sensing reconstruction of the image sequence, and sensitivity estimation with JSENSE. $T_{1\rho}$ quantification results from accelerated scans using the proposed method are evaluated using *in vivo* knee cartilage data from bi-lateral scans of three healthy volunteers.

Result— $T_{1\rho}$ maps obtained from accelerated scans (acceleration factors of 3 and 3.5) using the proposed method showed results comparable to conventional full scans. The $T_{1\rho}$ errors in all compartments are below 1%, which is well below the *in vivo* reproducibility of cartilage $T_{1\rho}$ reported from previous studies.

Conclusion—The proposed method can significantly accelerate the acquisition process of $T_{1\rho}$ quantification on human cartilage imaging without sacrificing accuracy, which will greatly facilitate the clinical translation of quantitative cartilage MRI.

Keywords

$T_{1\rho}$ mapping; cartilage imaging; compressed sensing; iterative support detection; principal component analysis; joint sensitivity estimation

INTRODUCTION

Magnetic resonance imaging (MRI) offers excellent soft-tissue contrast with high spatial resolution for visualizing cartilage in any plane. It has become an ideal tool for assessing cartilage degeneration in osteoarthritis, and evaluating treatment effectiveness. Recently, spin-lattice relaxation in the rotating frame, denoted by T1-rho ($T_{1\rho}$), has received considerable interest for the early identification of cartilage degeneration (1–3). $T_{1\rho}$ imaging can probe very low frequency interactions between motion-restricted water molecules and their local macromolecular environment (4). As a result, cartilage $T_{1\rho}$ imaging can detect early osteoarthritis prior to morphological or clinical changes based on the information associated with cartilage matrix changes (5). Multiple spin-lock times (TSLs) are usually required to generate $T_{1\rho}$ maps, which make the acquisition time demanding, especially during patient studies aimed at monitoring cartilage changes. The long image acquisition time introduces a series of complications such as increased motion artifacts, high radio-frequency power deposition, and patient discomfort. This challenge prevents wide spread use of quantitative cartilage $T_{1\rho}$ imaging in clinical settings.

Parallel imaging (6–9) and compressed sensing (CS) (10–12) are both fast imaging techniques that could potentially accelerate the acquisition speed of cartilage $T_{1\rho}$ imaging via k -space undersampling below the Nyquist rate. Parallel imaging has shown to accelerate cartilage $T_{1\rho}$ imaging by a factor of 2 (13). Although compressed sensing has been studied to accelerate T1 and T2 parametric imaging (14–23), and quite recently also $T_{1\rho}$ imaging (24–25), however, very few studies have investigated such techniques for cartilage $T_{1\rho}$ mapping (26,27). Most existing studies on parameter mapping using CS were performed on a large region of interest. In contrast, cartilage $T_{1\rho}$ imaging with CS acceleration is more challenging because cartilage is a thin and curved tissue. The signals associated with such regions of interest can be easily affected by typical CS artifacts. A recent study on cartilage $T_{1\rho}$ imaging (26) combines CS and parallel imaging using Sparse SENSE (28) to reconstruct images at each TSL separately, which showed significant $T_{1\rho}$ errors when acceleration factors were higher than 2.

Considering this reconstruction challenge, we combine an advanced compressed sensing (CS) based dynamic-imaging technique, k - t LAISD (Locally-Adaptive Iterative Support Detection), and an advanced parallel imaging technique, JSENSE, to achieve maximum acceleration of cartilage $T_{1\rho}$ imaging. In k - t LAISD, we improve upon k - t ISD (29) to detect support after projecting onto principal components using multiple local thresholds instead of a global one. The use of principal components as the sparsifying transform for parameter mapping has been demonstrated in several studies (16,19,20,22,30–32). It has been shown that parameter-weighted MR images can be represented in a much sparser form in the x -PCA domain than in the x - f domain (16). In parallel imaging, we incorporate coil sensitivity information into the reconstruction where the sensitivities are obtained using JSENSE (33), which iteratively estimates the sensitivity maps at different TSLs from reconstructed image sequences. Specifically, the reconstruction process alternates iteratively between local support detection in the space of principal components, CS reconstruction of the image sequence, and sensitivity estimation with JSENSE. The proposed method was validated using six *in vivo* human $T_{1\rho}$ cartilage datasets acquired from a bi-lateral scan on three

healthy volunteers. The $T_{1\rho}$ quantification calculated from the reconstructed images from the retrospectively accelerated acquisition shows good agreement with that from the fully sampled acquisition. The error percentage is negligible in all compartments.

METHODS

Data Acquisition

All MR examinations were performed on a 3 Tesla (3T) GE HDx whole-body MR scanner (General Electric Healthcare, Milwaukee, WI, USA) using a GE eight channel transmit/receive phased-array (PA) knee coil. Three healthy volunteers (aged between 30 to 34 years old) were recruited for this study. Six *in vivo* knee datasets from bi-lateral scans were acquired using a MAPSS (magnetization-prepared angle-modulated partitioned k -space spoiled gradient echo snapshots) $T_{1\rho}$ quantification pulse sequence developed previously (34,35). Specifically, the $T_{1\rho}$ preparation pulses contained continuous hard 90x (tip down pulses), spin lock pulses and 90-x (tip up pulses). Immediately after each magnetization preparation, multiple k -space lines (views per segmentation, VPS) were acquired. To eliminate the adverse impact of longitudinal relaxation on quantitative accuracy, radiofrequency (RF) cycling was applied. This RF cycling scheme also yields a transient signal evolution that is independent of the prepared magnetization. The filtering effect in k -space caused by transient signal evolution after each spin-lock is eliminated using the same variable flip angle train that generates a flat signal response (35). The pulse diagram is shown in Fig. 1.

The *in vivo* imaging protocols that were used to acquire these six datasets are: TSLs = 0/2/4/8/12/20/40/80ms; spin-lock frequency: 500Hz; matrix size PE $\times$ FE $\times$ Echo $\times$ Slice = 128 $\times$ 192 $\times$ 8 $\times$ 28; field of view = 140mm; slice thickness = 4mm. The experimental datasets are fully sampled and retrospectively undersampled using a variable density random sampling pattern along the phase encoding direction at each echo time with reduction factors of 3 and 3.5. Different sampling patterns are used at different TSLs, and the composite sampling locations from all TSLs cover all the phase encoding lines. The sampling pattern in k -TSL plane follows the 2D Poisson disc distribution to ensure temporal k -space coverage. The fully sampled portion in the center of k -space was 16% and 13% for acceleration factors of 3 and 3.5, respectively.

Image reconstruction

In k - t LAISD reconstruction with JSENSE, our objective is to combine the benefits from both compressed sensing and parallel imaging to maximize the acceleration of cartilage $T_{1\rho}$ imaging, and reconstruct the desired image sequence and sensitivities simultaneously. Taking advantage of the prior information that the image sequence is sparse in the principal component space along the TSL direction, our objective is to find coil sensitivity coefficients $\mathbf{a}$ and the principle components $\mathbf{p}$

$$\min_{\mathbf{a}, \mathbf{p}} \|\mathbf{p}\|_0 \quad \text{s.t.} \quad \|\mathbf{d} - \mathbf{E}(\mathbf{a})\mathbf{P}\mathbf{p}\|_2 < \varepsilon, \quad [1]$$

where $\mathbf{p}$ is a vector representing the desired $T_{1\rho}$ cartilage image series in the principal component space, $\mathbf{P}$ represents the inverse PCA projection matrix that maps $\mathbf{p}$ from the principal component space back to the original TSL space, $\mathbf{d}$ represents the acquired k -space data from all coils, and $\mathbf{E}$ represents the encoding matrix combining both the spatial Fourier transform along the phase encoding (PE) direction with the specified undersampling trajectory and coil sensitivity modulations with $\mathbf{a}$ as the unknown coefficients for coil sensitivities of all channels and TSLs. However, because $\|\mathbf{p}\|_0$ is nonconvex and combinatorial, solving [1] is impractical. A practical alternative is to replace $\|\mathbf{p}\|_0$ by $\|\mathbf{p}\|_1$ (known as basis pursue denoising, or BPDN), which is easy to solve but requires significantly more measurements. Here we use iterative support detection (ISD) (36) which proves to require fewer measurements than BPDN. As a result, the optimization problem in [1] is solved by alternating iteratively between local support detection in the principal component space, compressed sensing reconstruction of the image sequence, and sensitivity estimation with JSENSE.

Initialization—In the initialization step, a series of low resolution images are obtained from central k -space with Nyquist sampling density. Principal component analysis (PCA) is performed on these low resolution images to obtain the temporal principal components (PCs) used for sparsifying the image series in CS reconstruction. Initial coil sensitivity maps are computed from composite images generated by combining all undersampled k -space data from different TSLs to form a full set of k -space data for each channel. The adaptive array-combination technique (37,38) is used to smooth the sensitivity maps.

Because there is no prior information on the locations of significant elements in the principal component domain initially, conventional CS reconstruction is performed using

$$\mathbf{p}^{(0)} = \arg \min_{\mathbf{p}} \|\mathbf{d} - \mathbf{E}\mathbf{P}\mathbf{p}\|_2 + \lambda \|\mathbf{p}\|_1 \quad [2]$$

to obtain the initial estimate of the signal $\mathbf{p}^{(0)}$.

Local support detection in the sparse domain—We then apply support detection upon the previously reconstructed images in the sparse domain. Specifically, we improve upon k - t ISD (29) to detect the support in the principal component space using multiple local thresholds instead of a global one, named Locally-Adaptive Iterative Support Detection (LAISD). Specifically, different thresholds are applied on different pixel locations along the PCA direction according to the maximum intensity at that pixel. Let n represent the spatial index and N denote the total number of pixels. The reconstructed $T_{1\rho}$ cartilage image series in the x -PCA space at the i -th iteration can then be represented as a vector

$\mathbf{p}^{(i)} = [\vec{\mathbf{p}}_1^{(i)T} \quad \vec{\mathbf{p}}_2^{(i)T} \quad \dots \quad \vec{\mathbf{p}}_N^{(i)T}]^T$, where $\vec{\mathbf{p}}_n^{(i)}$ represents the PC coefficients of the n -th pixel. The support $\mathcal{T}^{(i)}$ is obtained by thresholding $\vec{\mathbf{p}}_n^{(i)}$ using a spatial-adaptive threshold $\beta_n^{(i)} = \mu^{(i)} \cdot \tau_n^{(i)}$ at each pixel n and combining the detected locations,

$$T^{(i)} := \bigcup_n \left\{ z: \left| \vec{\rho}_n^{(i)}(z) \right| > \beta_n^{(i)} \right\}, \quad [3]$$

where $\vec{\rho}_n^{(i)}(z)$ is the z -th element of the vector, $\tau_n^{(i)}$ is chosen adaptively as $\max(\left| \vec{\rho}_n^{(i)} \right|)$, and $\mu^{(i)}$ is a weighting parameter that decreases with iterations. Such locally adaptive thresholding can improve the quantification accuracy in those thin and low SNR cartilage compartments and avoid loss of the exponentially decaying signal at later TSLs by thresholding. In our implementation, $\mu^{(i)}$ is chosen as an exponential function of the iteration index, or $\mu^{(i)} = e^{-bi}$, $b > 0$. The choice of this exponential weighting is based on the results in k -t ISD (29). In our implementation, the decay rate b is set as 1.8.

Compressed Sensing Reconstruction with Detected Support—With the detected support, we are able to restrict all of the candidate sparse solutions of a conventional BPDN to a smaller subspace that includes the detected support $T^{(i)}$ from the previous iteration by default. To incorporate the detected support information into the compressed sensing optimization process, we exclude the part of the signal with known support from the cost function and update the signal ρ by a truncated ℓ_1 minimization. Mathematically, in the $(i+1)$ -th iteration of k -t LAISD, solving the signal ρ in x -PCA domain with known support $T^{(i)}$ is formulated as a truncated ℓ_1 minimization problem

$$\rho^{(i+1)} = \arg \min_{\rho} \|d - E P \rho\|_2 + \lambda \|\rho_{\Delta^{(i)}}\|_1, \quad [4]$$

where subscript $\Delta^{(i)}$ denotes the unknown support in the principal component space that excludes the known support $T^{(i)}$ obtained in support detection from the previous iteration, and λ is the regularization parameter that controls tradeoff between the data consistency and the sparsity of the signal. Once the nonzero locations in $\Delta^{(i)}$ are determined, the value of the entire signal can be obtained from the data consistency term.

An example of true support, detected support T , unknown support Δ , and missed support is shown in Fig. 2, where the true support is obtained from the fully sampled reference images using the same threshold. It can be seen that the proposed locally adaptive thresholding accurately detects support from not only most significant PCs but also less significant PCs. We also define the detected known support as $T = T_c + T_f$ where T_c is the support detected accurately shown in Fig. 2(d), and T_f is the false support shown in Fig. 2(e). It has been shown that truncated minimization with some false support can still reconstruct the underlying signals, provided that the size of the accurate support $|T_c|$ is larger than that of the false support $|T_f|$ (36), which is clearly seen in Fig. 2(d) and (e).

In our implementation, Eq. [4] is solved using the FOCUSS algorithm (39, 40) although many other algorithms are also applicable.

Sensitivity Update Using the Polynomial Model—To ensure the accuracy of the coil sensitivities used in reconstruction, we apply JSENSE to update the sensitivity functions

iteratively. Specifically, a polynomial parametric model is assumed for the sensitivity function at each channel ℓ and each TSL m :

$$s_{\ell,m}(x,y) = \sum_{p=0}^P \sum_{q=0}^Q a_{\ell,m,p,q} (x-\bar{x})^p (y-\bar{y})^q \quad [5]$$

where (x, y) denotes the location of a pixel, $(\bar{x}, \bar{y})$ denotes the central pixel coordinate, and $a_{\ell,p,q}$ are the coefficients of a polynomial for a specific channel, K denotes the order of the polynomial function. With $\mathbf{a}_{\ell,m}$ representing a component of the coefficient vector $\mathbf{a}$ in Eq. [1] for the ℓ -th channel and the m -th TSL, the coefficient vector for sensitivities can be updated by

$$\mathbf{a}_{\ell,m}^{(i+1)} = \arg \min_{\mathbf{a}_{\ell,m}} \|\mathbf{d}_{\ell,m} - \mathbf{E}(\mathbf{a}_{\ell,m}) [\mathbf{P}\boldsymbol{\rho}^{(i+1)}]_m\|_2^2, \quad \text{all } \ell \text{ and } m, \quad [6]$$

where $[\cdot]_m$ denotes taking a part of the vector that corresponds to the image of the m -th TSL. In our implementation, we use $P, Q = 6$ for both x and y . It is worth noting that the composite full k -space is only used for initializing the coil sensitivity maps. In solving Eq. [6], only the undersampled k -space data is used in the data fidelity term of the compressed sensing reconstruction.

Post-Processing

All post processing was performed using a program developed in-house (41). The $T_{1\rho}$ maps were constructed by the Levenberg-Marquardt mono-exponential fitting algorithm that fits the image intensity pixel to pixel to the equation:

$$I(\text{TSL}) \propto \exp(-\text{TSL}/T_{1\rho}). \quad [7]$$

$T_{1\rho}$ -weighted images were rigidly registered to the images with the shortest TSL using the VTK CISG Registration Toolkit (42) since these images yield the highest SNR among all acquired images. Cartilage was segmented semi-automatically into six compartments (LFC: lateral femoral condyle; LT: lateral tibia; MFC: medial femoral condyle; MT: medial tibia; Pat: patella; T: trochlea) based on edge detection and Bezier splines (43). To avoid erroneous inclusion of synovial fluid or other surrounding tissues, which have much higher $T_{1\rho}$ values in the region of interests (ROIs), the segmentation was corrected manually.

The flowchart of the post processing is demonstrated in Fig. 3.

Statistical Assessment

Statistical assessments were performed to evaluate the reconstruction quality of the proposed k -t LAISD method. Normalized root mean square error (nRMSE) was used to quantify the reconstruction error by calculating the pixel-wise difference between the reconstructed image and those obtained from fully sampled k -space using the following formula:

$$\text{nRMSE} = \sqrt{\frac{\sum_{n=1}^N (x^{\text{recon}}(n) - x^{\text{ref}}(n))^2}{\sum_{n=1}^N (x^{\text{ref}}(n))^2}}, \quad [8]$$

where N is the total number of pixels. The $T_{1\rho}$ quantification was evaluated using the mean $T_{1\rho}$ values from the accelerated acquisition for all pixels in the ROIs from all six knee datasets, and with their percentage of errors compared to the full acquisition. Let j denote the ROI compartment index, $j = 1, 2, \dots, 6$, d represent the dataset index, $d = 1, 2, \dots, 6$, and $\hat{T}_{1\rho}^{(j),(d)}$ denote the average $T_{1\rho}$ values of the j -th ROI compartment from the d -th dataset. The mean $T_{1\rho}$ value of the j -th ROI compartment of all six datasets was computed by

$$\bar{T}_{1\rho}^{(j)} = \frac{1}{6} \sum_{d=1}^6 \hat{T}_{1\rho}^{(d),(j)} \quad [9]$$

The percentage error for the j -th ROI compartment was calculated by

$$\text{Error Percentage}^{(j)} = \left| \frac{\bar{T}_{1\rho, \text{recon}}^{(j)} - \bar{T}_{1\rho, \text{ref}}^{(j)}}{(\bar{T}_{1\rho, \text{recon}}^{(j)} + \bar{T}_{1\rho, \text{ref}}^{(j)})/2} \right| \times 100\% \quad [10]$$

where $\bar{T}_{1\rho, \text{recon}}^{(j)}$ and $\bar{T}_{1\rho, \text{ref}}^{(j)}$ denote the mean $T_{1\rho}$ values calculated by Eq. [9] from accelerated and full scans for the j -th ROI compartment, respectively.

In order to evaluate the SNR degradation due to undersampling and reconstruction using the proposed method, an SNR comparison between the fully sampled reference images and the images reconstructed from the accelerated datasets was implemented for each of the six compartments for all TSLs. The SNRs in ROI were calculated using the following equation:

$$\text{SNR(dB)} = \frac{1}{M} \sum_{m=1}^M 20 \cdot \log_{10} \frac{\nu_{ROI}^{(m)}}{\sigma_{ROI}^{(m)}}, \quad [11]$$

where M denotes the total number of TSLs and ν_{ROI} and σ_{ROI} are the mean value and standard deviation of the pixels within the ROI.

The correlations of the parameters in each individual ROI measured from the fully sampled reference images and the reconstructions using accelerated data were also evaluated using linear regression plots. The agreement between the reference and the accelerated reconstructions was assessed by Bland and Altman analysis, which plots a scatter diagram of the difference against the average of the two measurements (44). A student's paired t -test was also performed to assess the significance of the difference ($P < 0.05$).

Comparison with Existing Methods

To demonstrate the advantage of applying locally-adaptive thresholding support detection in terms of SNR and the effectiveness of JSENSE in sensitivity estimation, we compared the

$T_{1\rho}$ quantification results from the proposed method (k - t LAISD JSENSE) with those obtained using five different reconstruction methods: k - t LAISD, k - t ISD (29), k - t FOCUSS (45, 46), and k - t SENSE (47) in x - f domain and x - PCA domain, where conventional SENSE is used for coil sensitivity estimation. The same random sampling patterns were used for the k - t LAISD, k - t ISD and k - t FOCUSS when reduction factor was fixed. The k - t lattice sampling pattern was used in k - t SENSE based method. The same portion of center k -space was fully sampled and used as the training signal (16% and 13% for acceleration factors of 3 and 3.5, respectively). The net reduction factor for k - t lattice sampling is defined as the ratio of the sampled PE lines over the total number of PE lines. The code for k - t FOCUSS was obtained from <http://bisp.kaist.ac.kr>.

RESULTS

Reconstruction Quality of k-t LAISD

The reconstructions of the *in vivo* human knee datasets with an acceleration factor R of 3 and 3.5 using the proposed method, along with the corresponding error images with respect to the fully sampled references are presented in Fig. 4. Images of different slices of a dataset at the second TSL are shown. The error images were scaled appropriately to better reveal differences. The nRMSEs are shown on the top left of each error image. It is seen that the reconstructions from accelerated scans have no notable artifacts. Although the errors become more visible with higher acceleration factors, they remain noise-like. No noticeable aliasing artifacts are observed from the images or the error maps. Low nRMSEs show good agreement with visual inspection.

Figure 5 shows the averaged intensity curves of all six compartments as a function of TSLs for both the accelerated reconstructions and reference from the same dataset. It is seen that the curves obtained from R = 3 and 3.5 agree well with those obtained from the fully sampled scans for all compartments. The consistent intensity curves for all TSLs also suggest the accuracy of $T_{1\rho}$ measurements.

$T_{1\rho}$ Quantification

Based on the reconstructed images at different TSLs, $T_{1\rho}$ maps were derived using the above-mentioned post-processing procedure. The estimated $T_{1\rho}$ maps overlaid with reconstructed cartilage images are shown in Fig. 6. The images are from two different volunteers and from two slices that cover all six compartments of interest. The color bar indicates $T_{1\rho}$ values in milliseconds. It can be seen that the reconstructed $T_{1\rho}$ maps show good agreement with those obtained from full acquisition in all compartments. The overall $T_{1\rho}$ maps obtained from both R = 3 and 3.5 are consistent with those obtained from full acquisition. Moreover, it is worth noting that the $T_{1\rho}$ maps obtained from both 3 $\times$ and 3.5 $\times$ accelerated acquisitions can accurately detect the raised $T_{1\rho}$ values in the medial and lateral femoral condyles (MFC and LFC) regions.

SNR is usually degraded due to reduced acquisition. To evaluate SNR degradation, the SNRs of the reconstructed images with R = 3 and 3.5 are compared with that of the fully acquired images for all six compartments (see Table S1 in Online Supplemental Material). It can be

seen that the SNRs of accelerated scans show good agreement with that of fully sampled ones with less than 1dB variation. It is worth noting that even for compartments with low SNR (e.g., the LFC, TRO and MFC with SNR below 10dB), the $T_{1\rho}$ quantifications from accelerated scans are still consistent with those from the reference.

Comparisons with Existing Methods

Figure 7 compares the $T_{1\rho}$ values in all compartments obtained using different methods. It is seen that k - t LAISD generates the closest map to that of the fully sampled dataset with the lowest mean error percentage (2.46%, 4.45%, 7.65%, 5.82% and 8.93% for k - t LAISD, k - t ISD, k - t FOCUS, k - t SENSE x -PCA and k - t SENSE x -f respectively).

The comparison between k - t LAISD with JSENSE and k - t LAISD with conventional SENSE shows that JSENSE significantly improves $T_{1\rho}$ estimation accuracy (0.72% for k - t LAISD with JSENSE and 2.46% for k - t LAISD with conventional sensitivity estimation). Accurate coil sensitivity estimation can reduce aliasing artifacts and noise and is thus critical to the reconstruction quality in SENSE based methods. JSENSE is able to update the coil sensitivity maps iteratively so as to improve the reconstruction. Figure 8 compares sensitivity maps estimated using the conventional method from the composite images, the low resolution images with and without smoothing (37, 38), and JSENSE (33). It can be seen that the sensitivity maps estimated from the composite images using the conventional method suffer from spatially dependent noise because the k -space data from large TSLs have low SNR. The sensitivity maps estimated from low resolution images have truncation effects. Although these noise and artifacts can be reduced to some extent by smoothing, the sensitivity maps from JSENSE are seen to be much cleaner and smoother. The improvement in the quantitative measure using JSENSE is evident in Fig. 7. In this study, we found that three JSENSE iterations are sufficient to provide accurate coil sensitivity maps.

We also compare the SNRs across six compartments in Table S2 in Online Supplemental Material. It can be seen that the proposed method not only achieves the lowest $T_{1\rho}$ errors, but also the highest SNR across all compartments among all methods.

$T_{1\rho}$ Statistical Assessment

The consistency of the $T_{1\rho}$ values between the accelerated and full scans was validated by statistical analysis. The mean values of all six datasets and their corresponding error percentages for all compartments were calculated and plotted in Fig. 9. The error percentage is low (<1%) in all compartments for both $R = 3$ and 3.5, which is far below the 5% acceptable reproducibility of *in vivo* cartilage $T_{1\rho}$ quantification reported in (5). Compared to other compartments, LFC and PAT have comparatively higher error percentage (0.84% and 0.87% for $R = 3$; 0.79% and 0.96% for $R = 3.5$), which is consistent with observations of the overlaid $T_{1\rho}$ maps. The overall mean error for an acceleration of 3 is 0.63% and 0.64% for an acceleration of 3.5. It is worth mentioning that although some compartments present higher error percentage in $R = 3$ than in $R = 3.5$, the overall observations show that results from $3.5\times$ acceleration present larger error variances than those in $3\times$ acceleration.

The correlations between $T_{1\rho}$ values obtained with fully sampled and accelerated scans were further evaluated using linear regression and Bland and Altman plots, and the results are

shown in Fig. 10. Overall, both reconstructions obtained from accelerated scans show good agreement with the images from full scans. In the linear regression model, the R square values for both reconstructions with acceleration factor of 3 and 3.5 are close to 1 (0.9963 for $3\times$ acceleration and 0.9938 for $3.5\times$ acceleration). The Bland and Altman analysis plot (right of Fig. 10) compares the $T_{1\rho}$ values calculated from both the accelerated and full scans. The plots show that the differences in the $T_{1\rho}$ value are within twice the standard deviation range (2SD) ($SD = 0.263$ for $3\times$ acceleration and 0.289 for $3.5\times$ acceleration). No statistically significant differences were observed between the $T_{1\rho}$ values measured across the subjects without acceleration (38.6 ± 0.95 msec) and with acceleration (38.8 ± 0.95 msec for $3\times$ acceleration and 39.0 ± 0.95 msec for $3.5\times$ acceleration).

DISCUSSION

This work specifically studies the acceleration of $T_{1\rho}$ cartilage imaging using compressed sensing. Cartilage $T_{1\rho}$ mapping is different from other parameter mapping applications in several aspects. Firstly, the region of interest is very small compared to other parts of the body. Smoothness constraints such as total variation are not applicable to such a thin and small ROI. Secondly, not all the data, such as low-intensity bone area that is adjacent to cartilage, fits into the $T_{1\rho}$ parametric model due to the very low SNR in the later TSLs. So the model-based approaches such as (20) are not applicable here. Thirdly, specific ROIs need to be treated differently from other low SNR regions. Conventional reconstruction methods that treat all spatial locations equally cannot ensure high fidelity at the target ROIs. Finally, quantitative $T_{1\rho}$ values, not the quality of individual images, are of particular importance in cartilage $T_{1\rho}$ mapping studies. Our method is specifically designed to address the unique challenges in $T_{1\rho}$ cartilage imaging.

Employing support detection in a compressed sensing reconstruction framework has been previously presented to accelerate dynamic MR cardiac cine imaging (29). The improvement of our approach over the one in (29) lies mainly that the proposed k - t LAISD adaptively applies local thresholds on the principal components to better detect the support of low-contrast features from the background noise. In cartilage $T_{1\rho}$ images, most of the compartments are thin in size, with relatively low pixel intensity values, especially in the images with long TSLs. Without proper thresholding, signals at later TSLs are too low to be reconstructed faithfully. As an advanced CS reconstruction method, k - t LAISD not only adapts the threshold through iterations (like k - t ISD does), but also chooses different thresholds at different pixels. This dual adaptability nature of threshold along pixel locations and iteration number allows the threshold to be chosen in the way such that it is large enough to avoid false support detection due to noise, and small enough to not miss the true support.

In previous work (13), images at different TSLs are reconstructed independently. Although such images may still be acceptable, $T_{1\rho}$ quantification has large errors at acceleration factors greater than 2. Our proposed method addressed the challenges in cartilage $T_{1\rho}$ mapping by integrating JSENSE and compressed sensing with iterative locally-adaptive thresholding support detection in the PCA domain. Our results show high fidelity in $T_{1\rho}$ quantification between accelerated and full-sampled data at high acceleration factors of 3

and 3.5. Using such an advanced acceleration technique, we can either reduce acquisition time significantly, which will expedite clinical translation of cartilage quantitative MRI or increase the number of TSLs for study of bi-exponential models.

The current implementation of the k - t LAISD method has a few limitations that will be addressed in future work. First, the use of JSENSE increases the computational burden of the proposed method. In our current implementation, the computation time is about 3847 seconds to perform each JSENSE iteration for the data size $128(\text{PE}) \times 192(\text{FE}) \times 8(\text{Channel}) \times 28(\text{Slices})$ on a Dell workstation with Intel 3.40GHz CPU and 16GB RAM running MATLAB 2012a. This is in contrast to 612 seconds without JSENSE on the same workstation. The computational speed can be improved by replacing Matlab with C implementation or using a GPU. Second, the method involves choosing the threshold as a function of iterations as well as spatial locations which governs the detection of the support for compressed sensing reconstruction. Our current choice is to empirically set the decay rate b proportional to the $T_{1\rho}$ curve decay rate so as to preserve features well. The same decay rate was used for all six datasets and has shown consistent performance. Further evaluations on different patients and different imaging settings are needed to validate the choice of the parameter. Third, a proper choice of regularization parameter λ is critical to reconstruction quality. In our study, the regularization parameter was manually tuned for optimal algorithm performance, but this was only possible for known ground truth. Although choosing the optimal regularization parameter is still an open question, there are a number of methods (48) that can be applied such as the L-curve method and the generalized cross-validation method.

In our experiments, a MAPSS sequence was used to acquire the full k -space data for the $T_{1\rho}$ image series. Although all datasets were retrospectively undersampled in this study, the actual prospective undersampling is not expected to interfere the MAPSS sequence and thereby will not change the conclusion of this study. As part of future work, an actual CS undersampling pattern will be implemented in the MAPSS sequence and a 3D version of the reconstruction scheme will be developed to further improve the speed and accuracy of $T_{1\rho}$ quantification.

CONCLUSION

We have presented a fast $T_{1\rho}$ mapping method for cartilage imaging based on compressed sensing with locally adaptive iterative support detection and parallel imaging with JSENSE. Our results demonstrate the feasibility of accelerating $T_{1\rho}$ quantification in human cartilage by factors up to 3.5. The proposed method achieves a fitting error less than 1% which is much less than the 5% *in vivo* reproducibility of cartilage $T_{1\rho}$ quantification. Future studies will explore accelerated cartilage $T_{1\rho}$ quantifications on patients with cartilage degenerations to validate the clinical significance of the developed technique. Accelerated acquisitions of relaxation time quantification in cartilage will significantly facilitate the clinical translation of quantitative cartilage MRI.

Online Supplemental Material

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Fig. 1. The pulse diagram of the MAPSS (magnetization-prepared angle-modulated partitioned k -space spoiled gradient echo snapshots) $T_{1\rho}$ quantification pulse sequence.

Fig. 2.

Maps of support in x - PCA space. (a): True support. (b): Detected (known) support T . (c): Unknown support which excludes T . (d): Detected support T_C that is correct. (e): Detected support T_F that is wrong. (f) Missed support. Support is shown in white. An acceleration factor of 3 is used.

Fig. 3.

The post processing process: $T_{1\rho}$ -weighted images were rigidly registered to the images with the shortest TSL using VTK CISG Registration Toolkit. The $T_{1\rho}$ maps were constructed by the Levenberg-Marquardt mono-exponential fitting algorithm that fits the image intensity pixel to pixel. The cartilage were segmented semi-automatically into six compartments (LFC: lateral femoral condyle; LT: lateral tibia; MFC: medial femoral condyle; MT: medial tibia; Pat: patella; T: trochlea) based on edge detection and Bezier splines. All segments were manually corrected to avoid erroneous inclusion of synovial fluid or other surrounding tissues.

Fig. 4.

The reconstruction results of the *in vivo* human knee using *k-t*LAISD with acceleration factors of 3 and 3.5. Different slices from a volunteer are shown. Error images were scaled accordingly to better reveal the difference. Normalized root mean square errors are shown on the left top corner of each error image.

Fig. 5.

Averaged signal-intensity curves as a function of TSLs for all six ROI compartments. The curves represent the reconstructions from full acquisition and reduced acquisition using our technique with acceleration factors of 3 and 3.5. Both curves are consistent with that from full scan for all compartments.

Fig. 6.

$T_{1\rho}$ maps overlaid on the knee cartilage images. Maps from acceleration factors of 3 and 3.5 are compared with those from the full scan as the reference. Two different slices are shown to include all six compartments. The $T_{1\rho}$ values obtained from the accelerated scans are consistent with those from the full scan.

Fig. 7.

Top: The mean $T_{1\rho}$ values of all six cartilage compartments of a volunteer from fully sampled, k - t LAISD with JSense, and k - t LAISD, k - t ISD and k - t FOCUSS with conventional SENSE. **Bottom:** Corresponding percentage errors of the $T_{1\rho}$ values. It can be seen that the reconstructions from k - t LAISD with JSense achieves the lowest error percentage compared with the other three methods.

Fig. 8.

Coil sensitivity maps of a single coil estimated using different methods. Regions with low signal intensity (background and bone) are removed for better visualization. **(a)**: Conventional SENSE with composite images without smoothing. **(b)**: Conventional SENSE with composite images with smoothing. **(c)**: Conventional SENSE with the low resolution images without smoothing. **(d)**: Conventional SENSE with the low resolution images with smoothing. **(e)**: JSENSE.

Fig. 9.

Top: The mean $T_{1\rho}$ values of all six datasets from fully sampled image and images with $R = 3$ and 3.5 . Results from all six compartments are shown. **Bottom:** Corresponding percentage errors of the mean $T_{1\rho}$ values. It can be seen that the reconstructions from accelerated scans have errors below 1% in all compartments. The results with $R = 3.5$ show larger variations than those with $R = 3$.

Fig. 10.

Left: The linear regression plot of $T_{1\rho}$ values for fully sampled reference, and accelerated reconstructions with $R = 3$ and 3.5 . It shows that the $T_{1\rho}$ values from the accelerated reconstructions strongly correlate with those from reference ($R^2=0.9963$ for $3\times$ acceleration and $R^2=0.9938$ for $3.5\times$ acceleration). **Right:** The Bland-Altman plot of the $T_{1\rho}$ values difference vs. the average $T_{1\rho}$ values for $R = 3$ (Bias = -0.1055 , 95% limits of agreement [$-0.610, 0.420$]) and $R = 3.5$ (Bias = -0.129 , 95% limits of agreement [$-0.695, 0.437$]).