NOTE

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Auto-Calibration Approach for k–t SENSE

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Purpose: The goal of this work is to increase the spatial resolution of training data, used by reconstruction methods such as k–t SENSE in order to calculate the missing data in a series of dynamic images, without compromising their temporal resolution or acquisition time.

Theory: The k-t SENSE method allows dynamic imaging at high acceleration factors with high reconstruction quality. However, the low resolution training data required by k-t SENSE may cause undesired temporal filtering effects in the reconstructed images.

Methods: In this work, a feedback regularization approach is applied to realize auto-calibration of the k-t SENSE algorithm. To that end, a full resolution training data set is calculated from the accelerated data itself using a TSENSE reconstruction. The reconstructed training data are then fed back for the actual k-t SENSE reconstruction. For evaluation of our approach, temporal filtering effects are quantified by calculating the modulation transfer function and noise measurements are done by Monte-Carlo simulations.

Results: Computer simulations and cardiac imaging experiments demonstrate an improved temporal fidelity of auto-calibrated k-t SENSE compared to standard k-t SENSE.

Conclusion: Auto-calibrated k-t SENSE provides high quality reconstructions for dynamic imaging applications. **Magn Reson Med 000:000–000, 2013. © 2013 Wiley Periodicals, Inc.**

Key words: dynamic magnetic resonance imaging; parallel imaging; k–t SENSE; auto-calibration; temporal filtering

Parallel magnetic resonance imaging reduces acquisition times by the subsampling of k-space. Dedicated reconstruction algorithms make use of spatial coil sensitivity variations from a multichannel receive array in order to remove the aliasing artifacts caused by the subsampling; generally, they can be enclosed into two groups: methods in which the estimation of the coil sensitivity maps is explicit [e.g., SENSE (1)] and methods in which the calculation of the coil sensitivity maps is inherent in the reconstruction process [e.g., GRAPPA (2)]. All parallel magnetic resonance imaging methods require prior information about the spatial coil sensitivity patterns; this information is typically obtained by an extra scan or embedded in the accelerated acquisition by applying a variable density acquisition scheme (i.e., the k-space center is fully sampled and the k-space periphery is subsampled).

In dynamic applications, a full field-of-view reference image with full resolution can be obtained when a time-interleaved acquisition scheme is used [TSENSE (3), Auto-SENSE (4), TGRAPPA (5)]. The coil sensitivity information is then extracted from this reference image and hence no extra acquisitions are required, if the coil configuration does not present big variations over the time.

Dynamic parallel MRI methods such as k-t SENSE (6) exploit not only spatial coil sensitivity variations but also make use of spatio-temporal correlations to separate the aliased signals. A priori information about spatio-temporal correlations is obtained by means of a training data set. Traditionally, the training data consist of several central k-space lines acquired in a separate scan prior to the subsampled data acquisition. However, this training data may be susceptible to misregistration (e.g., due to patient motion) or may have different contrast due to administration of GdDTPA for dynamic MRA, for example. Alternatively, the training data may be acquired interleaved during the accelerated scan by using a variable density acquisition scheme (7). However, the extra training lines in both acquisition schemes require additional acquisition time. Also, the limited spatial resolution of the training data may result in temporal filtering effects (temporal blurring) in the reconstructed images (8). It has been demonstrated that the temporal filtering process depends on the spatial resolution of the training data; typically, the higher the spatial resolution of the training data the better the k–t SENSE reconstruction quality (8). Parallel imaging can be used to increase the spatial resolution of the training data (9,10) but the achievable acceleration is reduced by scanning the extra training lines and the spatial resolution of the training data is still limited.

In this work, we propose an auto-calibration approach for k–t SENSE that is based on feedback regularization (11). To that end, a TSENSE (3) reconstruction is applied to the subsampled data, and the resulting images are then utilized as training data for k–t SENSE. It is important to note, that the acquisition of extra fully encoded training lines is not needed because the training data are generated with full spatial and temporal resolution from the subsampled data itself.

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The performance of the auto-calibrated k–t SENSE reconstruction is compared to conventional k–t SENSE method. To quantify temporal filtering effects, the modulation transfer functions (MTFs) (12) are calculated and the noise characteristics are investigated by means of Monte-Carlo simulations.

It is demonstrated that auto-calibrated k–t SENSE leads to reduced temporal filtering effects in the reconstructed images when compared to conventional k–t SENSE.

THEORY

Review: k–t SENSE

It has been demonstrated that in a temporal series of images there exist correlations between points at different positions in k-space and at different temporal frequencies (6). These data correlations are exploited by reconstruction methods such as UNFOLD (13), k-t BLAST, or k-t SENSE (6) which use temporally shifted acquisition schemes.

In the following, we consider the data in the (x,y,f) domain where f denotes the temporal frequency. R-fold subsampling in a temporally shifted fashion results in aliasing in which R locations of the true object data (ρ) in the (x,y,f) domain are mapped into a single pixel in the aliased data (ρ_{alias}).

The k–t SENSE method calculates the vector (ρ_{recon}) of unaliased (x,y,f) signals using a regularized solution:

$$\rho_{recon} = (S^H \psi^{-1} S + \lambda (M^2)^{-1})^{-1} S^H \psi^{-1} \rho_{alias} \qquad [1]$$

where S is the sensitivity encoding matrix, ψ is the noise covariance matrix of the receiver coil array, M^2 is the matrix containing the regularization coefficients (typically a diagonal matrix) and λ is the regularization parameter that determines the degree of regularization. In this work, the parameter λ for the different data sets was empirically chosen so that the reconstructed data show low temporal filtering but improved signal-to-noise ratio (SNR) compared to standard TSENSE.

The diagonal elements of M are the pixel values from the training data set. Principally, M acts as a filter approximating the true signal values in (x,y,f) space. The information contained in this matrix should be as close as possible to true object (ρ) to obtain an accurate reconstruction.

Auto-Calibrated k–t SENSE

The principal goal is to obtain images with high spatial and temporal resolution to be used as training data in k–t SENSE without acquiring extra data. Here, we estimate the training data from the subsampled data set itself.

Principally, the reconstruction consists of three calculation stages (Fig. 1):

I. Coil sensitivity calculation using a corrected temporal average
II. Construction of the training data using TSENSE
III. Final conventional k–t SENSE reconstruction

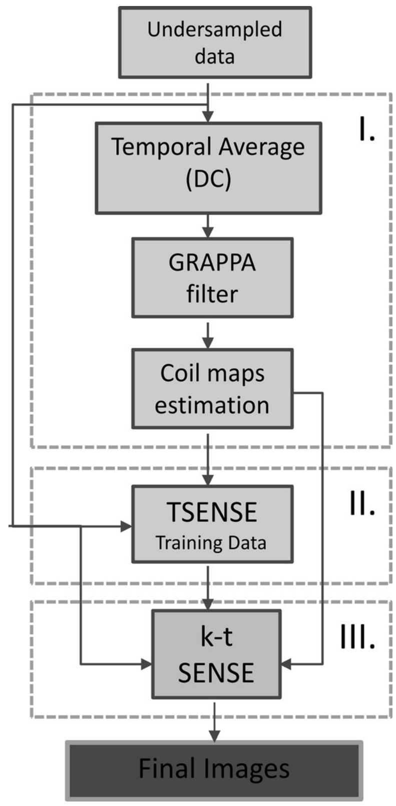

FIG. 1. Scheme of auto-calibrating k–t SENSE process consisting of three blocks: In the I. block the coil maps are estimated, in the II. block TSENSE is used to construct the training data and in block III. conventional k–t SENSE is applied to get the final images.

Coil Sensitivity Calculation Using a Corrected Temporal Average

Looking at all time-points in the temporally shifted sampling pattern, every k-space location is acquired at least once. This particular characteristic allows the calculation of a full field-of-view image with full spatial resolution by temporal integration. The resulting image is known as temporal average (or direct current, DC). The DC image contains the stationary information of the dynamic image series and it is located at the null temporal frequency. Stationary objects in the image generate signal only at the DC term. It is important to note that the DC obtained by temporal integration of subsampled data (DC_{under}) and the DC obtained from fully sampled data (DC_{full}) are different because nonstationary components lead to a DC image with aliasing artifacts (14). To estimate an aliasing-free DC image, a GRAPPA filter is applied to the DC_{under} signal (14) and spatial coil sensitivity maps are extracted from the resulting image.

Construction of the Training Data Using TSENSE

Using coil sensitivity information from stage I, a TSENSE (3) reconstruction is applied to the subsampled data. The resulting images are used as the training data for the k–t SENSE reconstruction stage.

Final Conventional k–t SENSE Reconstruction

Using the coil sensitivity maps from stage I and training data from stage II, the final k–t SENSE reconstruction is performed to obtain the final images.

METHODS

Simulations

To produce the simulated data, a numerical model with a matrix size of 100 × 100, was multiplied by coil sensitivity maps from a circular eight-channel receive array obtained by Biot-Savart calculations. Complex Gaussian noise was added to each channel.

The simulated data sets were retrospectively subsampled by a factor of $R = 5$. The applied sampling pattern was the optimized Cartesian interleaved scheme for acceleration factor 5 according to reference (15), where the acquired data were shifted two phase encoding lines over one time step, and then reconstructed using auto-calibrated k–t SENSE and conventional k–t SENSE. The conventional reconstructions were performed using training data sets with low resolution (21 central k-space lines) and full resolution as reference data. For cardiac applications, according to Hansen et al. (8), the recommended amount of reference training data lines is at least 10 in order to ensure sufficient reconstruction quality, without compromising the temporal resolution of the acquired data and their quality. Here, we used 21 k-space central lines as training data to perform the conventional k–t SENSE to obtain images with moderate temporal blurring. Although this amount of central lines is relatively high, our goal is to demonstrate the existence of temporal filtering using limited amount of training data.

In Vivo Experiments

In vivo prospectively gated, segmented cardiac cine experiments (bSSFP sequence with parameters: echo time = 1.4 ms, pulse repetition time = 2.7 ms, flip angle = 50°, 32 time frames and a matrix size of 192 × 150, field-of-view of 350 × 263 mm^2, 32 receiver channels) were performed on a 1.5 T whole body scanner (Siemens Medical Solutions, Erlangen, Germany). The data were retrospectively subsampled ($R = 5$). As in the simulation the optimized Cartesian interleaved sampling scheme for acceleration factor 5 was used. Both conventional and auto-calibrating k–t SENSE reconstructions were performed. The conventional reconstructions were done using training data sets with low resolution (21 k-space central lines) and full resolution.

Additionally a real time free-breathing experiment was performed using a (bSSFP) sequence with parameters: acceleration factor $R = 4$, sampling pattern based on a Cartesian interleaved scheme where the acquired data were shifted one phase encoding line over one time step, echo time = 1.4 ms, pulse repetition time = 2.7 ms, flip angle = 50°, 32 time frames, a matrix size of 92 × 192, field-of-view of 350 × 263 mm^2, eight receiver channels. The experiment was performed without the acquisition of the training data. As a consequence only auto-calibrating reconstruction methods could be applied to reconstruct the data. In this work, we performed TSENSE and auto-calibrated k–t SENSE reconstructions.

Data Reconstruction and Evaluation

All reconstructions were done off-line using the MATLAB (Mathworks, Natick, MA) programming environment. Simulated and in vivo data were reconstructed

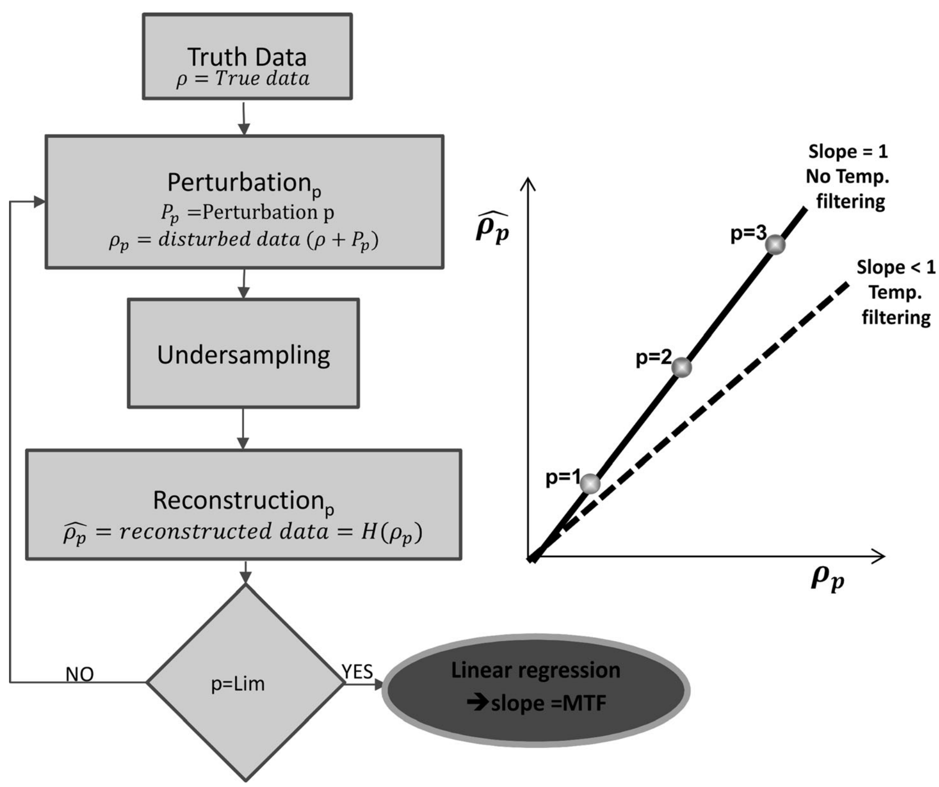

FIG. 2. This scheme illustrates the MTF calculation process, which is based on the perturbation approach. For each temporal frequency point, the reconstructed data $\hat{\rho}_p$ are plotted versus the disturbed data ρ_p obtaining the graph shown at the right hand side of the figure. Subsequently, these points are fitted into a line. The slope represents the MTF at that temporal frequency point.

using conventional and auto-calibrated k–t SENSE with different regularization values λ (see Eq. [1]) to observe the temporal filtering effect produced by the various regularization degrees.

Both reconstruction methods were compared by evaluating their MTFs (12). For dynamic MRI applications, the MTF describes the relation between the true signal M_{true} and the reconstructed signal M_{recon} at a given temporal frequency:

$$\mathrm{MTF}\,(f) = \frac{M_{\mathrm{recon}}\,(f)}{M_{\mathrm{true}}\,(f)} \qquad [2]$$

It is therefore a quantitative measure for temporal filtering effects caused by the reconstruction algorithms. The MTF can be assessed by a perturbation approach (12). This process is described in Figure 2. To that end, perturbations (P_{p}) are added to the true signal (ρ), resulting in the disturbed data ρ_{p}. The disturbed signal or "new" true signal is then subsampled and reconstructed to yield the final signal ($\hat{\rho}_{\mathrm{p}}$). The reconstructed signal ($\hat{\rho}_{\mathrm{p}}$) versus the value of the disturbed data (ρ_{p}) are plotted at each temporal frequency. This process is repeated with different linearly increasing perturbations. The slope of the fit to these points (ρ_{p},$\hat{\rho}_{\mathrm{p}}$) represents the

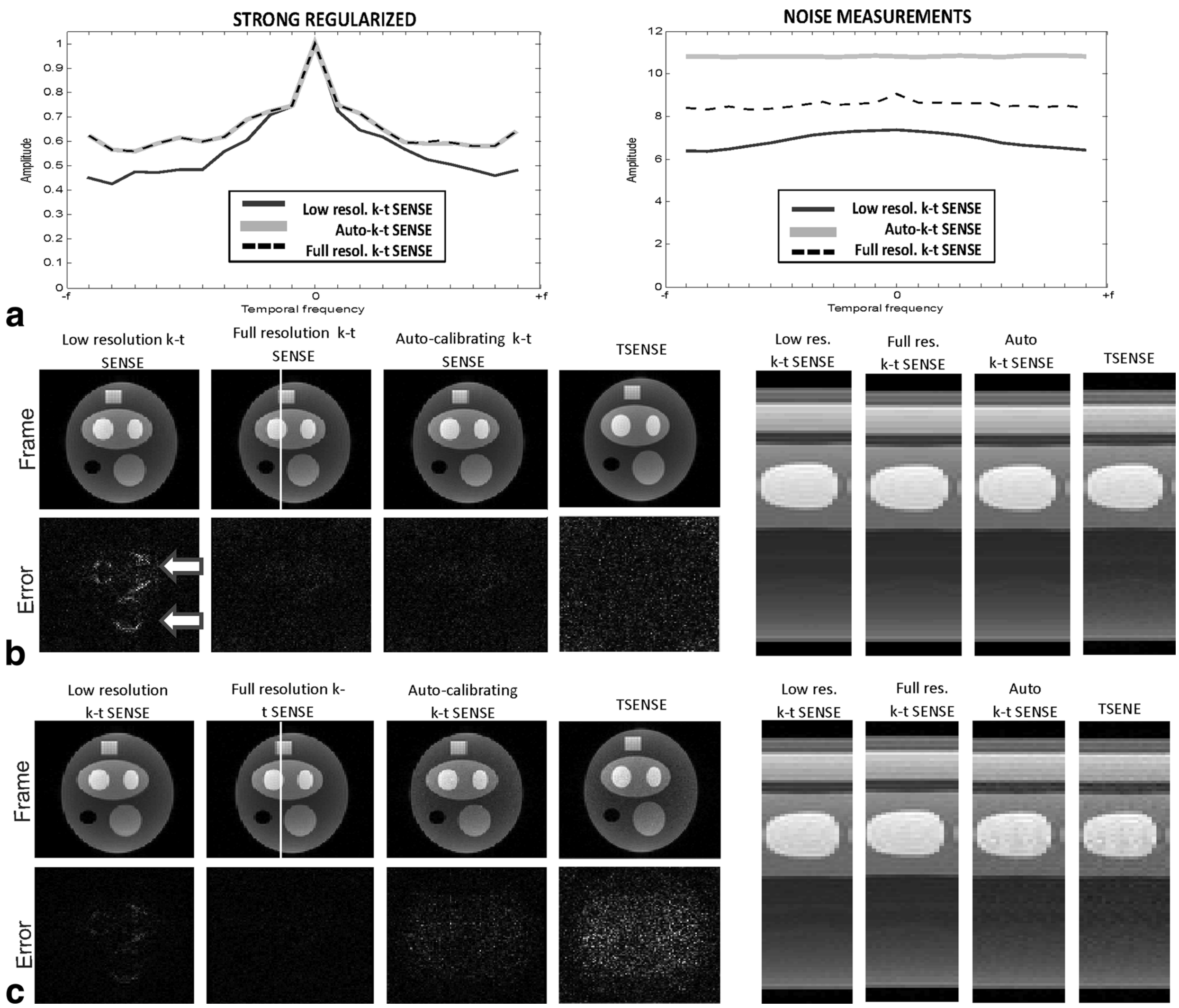

FIG. 3. **a**: MTFs of: conventional k–t SENSE reconstructions of simulated data (acceleration factor $R = 5$) using fully sampled k-space as training data (black discontinuous line), using 21 central k-space lines (dark gray line) and auto-calibrating k–t SENSE reconstruction (light gray line) with a strong regularization. To the right, the resulting noise levels versus the temporal frequency are plotted for the three different reconstruction methods respectively. **b**: An exemplary frame of the reconstructions of $R = 5$ subsampled data with moderate noise level performed by: conventional k–t SENSE reconstruction using 21 central k-space lines (first column) and using fully sampled k-space as training data (second column), auto-calibrating k–t SENSE reconstruction (third column) and TSENSE reconstruction (last column). The errors with respect to the reference data are shown on the bottom of each reconstruction. M-mode plots along the white line in image domain of the reconstructions are also shown. **c**: An exemplary frame of the reconstructions of $R = 5$ subsampled data with higher noise level performed by: conventional k–t SENSE reconstruction using 21 central k-space lines (first column) and using fully sampled k-space as training data (second column), Auto-calibrating k–t SENSE reconstruction (third column) and TSENSE reconstruction (last column). The errors with respect to the reference data are shown on the bottom of each reconstruction. Again, m-mode plots along the white line in image domain are shown to the right.

MTF. A perfect reconstruction has a slope of 1, meaning that the reconstructed data do not present temporal filtering (i.e., $M_{\mathrm{recon}}(f) = M_{\mathrm{true}}(f)$). Slopes smaller than 1 correspond to temporal filtering.

In this work, 2D MTFs were calculated for conventional and auto-calibrated k–t SENSE methods as described in reference (12) and then averaged along the k_y-direction. Averaging along the k_y-direction was performed for displaying the data, because the MTF functions present only small variations along this dimension.

Additionally, the noise level was evaluated using Monte-Carlo simulations. To that end, the acquired data were replaced by complex Gaussian random numbers. These new data were subsampled and reconstructed by conventional and auto-calibrated k–t SENSE. This process was repeated 30 times for different noise data and its variance was calculated. The ratio between the variances of these reconstructions $\hat{\rho}_R$ and the reconstructions of the fully sampled data $\hat{\rho}_1$, is given by:

$$N(k_y, f) = \sqrt{\frac{\sum_{k_x} \mathrm{var}\{\hat{\rho}_R(k_x, k_y, f)\}}{\sum_{k_x} \mathrm{var}\{\hat{\rho}_1(k_x, k_y, f)\}}}. \quad [3]$$

RESULTS

Simulations

MTFs of auto-calibrated and conventional k–t SENSE for simulated data (acceleration factor $R = 5$) are shown on the left side hand of Figure 3a. The light gray curve represents the MTF of the auto-calibrated k–t SENSE method, the dark gray and discontinuous black curves represent the MTF of the conventional k–t SENSE using training data with low resolution and full resolution training data respectively.

The MTFs disclose the temporal filtering produced by auto-calibrated and conventional k–t SENSE reconstructions. As expected, the MTFs of conventional k–t SENSE using low resolution images as training data show more attenuation at frequencies outside the DC term, implying higher filtering and thus temporal blurring when compared to auto-calibrated and conventional k–t SENSE with full resolution training data. Note that auto-calibrated k–t SENSE behaves similar in terms of temporal filtering as conventional k–t SENSE with full resolution training data. The noise measurements of these reconstruction methods were calculated and are displayed on the right side of Figure 3a.

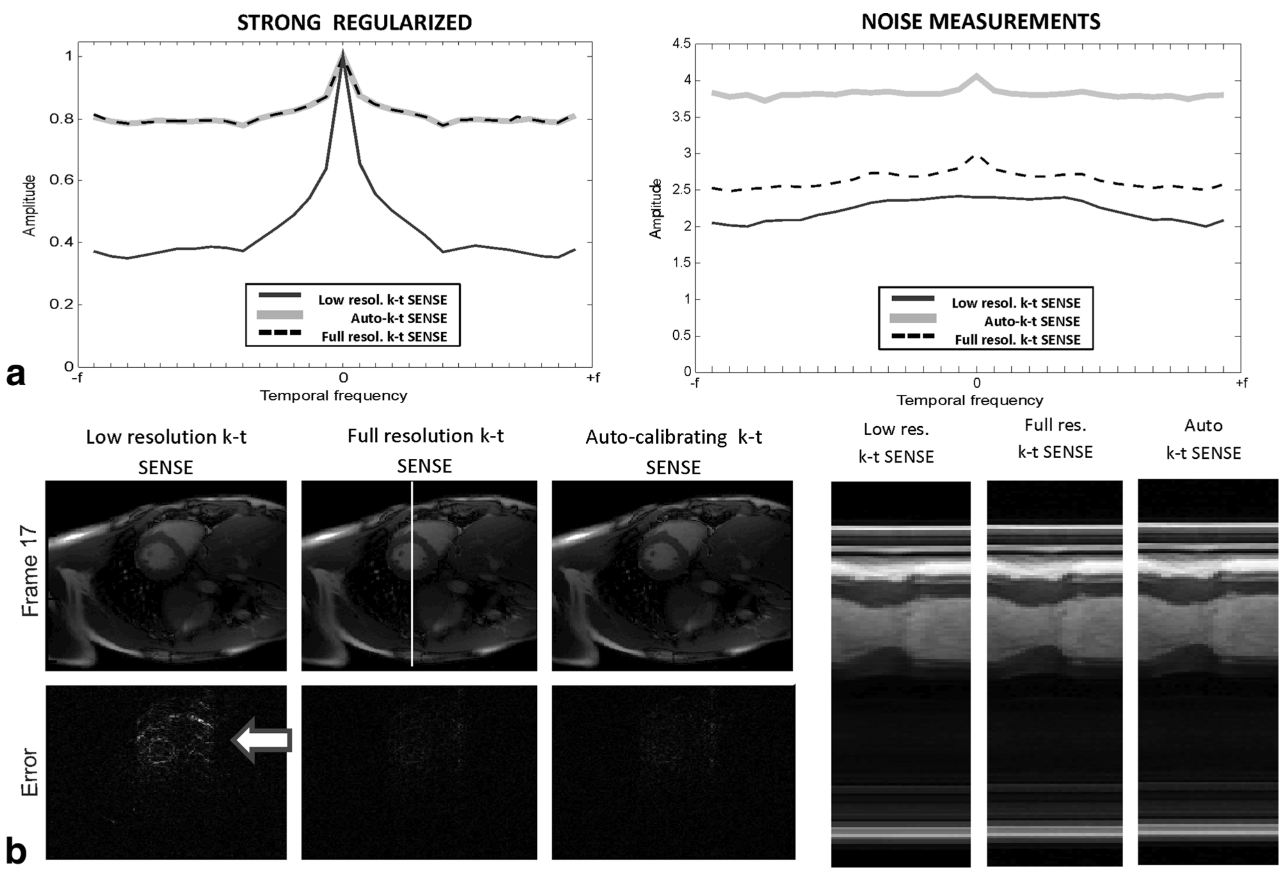

FIG. 4. **a**: MTF of: conventional k–t SENSE reconstruction of $R = 5$ simulated data using fully sampled k-space as training data (black discontinuous line), using 21 central k-space lines (dark gray line) and auto-calibrating k–t SENSE reconstruction (light gray line) with strong regularization. At the right side the resulting noise levels versus the temporal frequency are shown. **b**: Exemplary frame of the reconstructions of $R = 5$ undersampled data using strong regularization performed by: conventional k–t SENSE reconstruction data using 21 central k-space lines (left column) and using fully sampled k-space as training data (middle) and auto-calibrating k–t SENSE reconstruction (right column). The errors with respect to the reference data are shown on the bottom of each reconstruction. The m-mode plots along the white line in image domain of the reconstructions are also shown.

Spatial errors are displayed in Figure 3b (left) on the bottom of the reconstructed images. The arrows point out the temporal blurring effect produced by conventional k–t SENSE due to the lack of spatial resolution of the training data; regions containing high frequency motion are highly affected. Analyzing the noise measurements (Figure 3a, right), one can find that auto-calibrated k–t SENSE has a reduced SNR. The noise amplification in the reconstructions is more visible adding higher noise levels to the simulated data, see Figure 3c.

In Vivo Experiments

CINE Experiment

Figure 4a (left) shows the MTFs of the three reconstruction methods using a strong regularization level. Again the reconstructions of conventional k–t SENSE with low resolution training data result in the highest temporal filtering. In Figure 4b (left), reconstructed images are displayed. The blurring effect becomes evident in conventional k–t SENSE images in frame 17 and can also be observed at the m-mode plot in the Figure 4b (right). The myocardium appears sharper in auto-calibrated k–t SENSE and full resolution k–t SENSE reconstructions. The arrow points out the artifacts produced by the lack of spatial resolution in the training data in conventional k–t SENSE reconstructions with low resolution training data.

The noise measurements of in vivo data present similar behavior as in the simulated data (see Figure 4a, right).

Free Breathing Experiment

Auto-calibrated k–t SENSE and TSENSE reconstructions of the free-breathing subsampled data ($R=4$) are shown in Figure 5. From here one can clearly see that the auto-calibrated k–t SENSE reconstructions present higher SNR than the reconstruction with TSENSE. In Figure 5, the m-mode plots illustrate that both reconstructions do not present blurring artifacts caused by temporal filtering. It is also evident that the SNR of auto-calibrated k–t SENSE reconstructions is higher than the SNR of the TSENSE reconstructions.

Neither the noise measurements nor the MTFs of the reconstructions were calculated due to the lack of fully sampled reference data. As the training data set also was not acquired, conventional k–t SENSE reconstruction were not performed.

DISCUSSION

The training data play an important role in k–t SENSE reconstructions. For an optimal reconstruction, the training data should be consistent with the subsampled data. Furthermore, high spatial resolution of the training data is important to avoid strong temporal filtering effects. Here, we have presented a feedback regularization approach for k–t SENSE. The training data are obtained from the subsampled data by an additional TSENSE reconstruction prior to the final k–t SENSE reconstruction. The training data have full spatial resolution and therefore minimize the temporal filtering effect in the k–t SENSE reconstructed images. An additional advantage of this method is the elimination of the training data acquisition.

The use of the TGRAPPA reconstruction technique instead of TSENSE for obtaining the training data and the coil sensitivity maps for k–t SENSE is also possible. However, the reconstructions using TGRAPPA result in lower SNR affecting the quality of the k–t SENSE reconstructions.

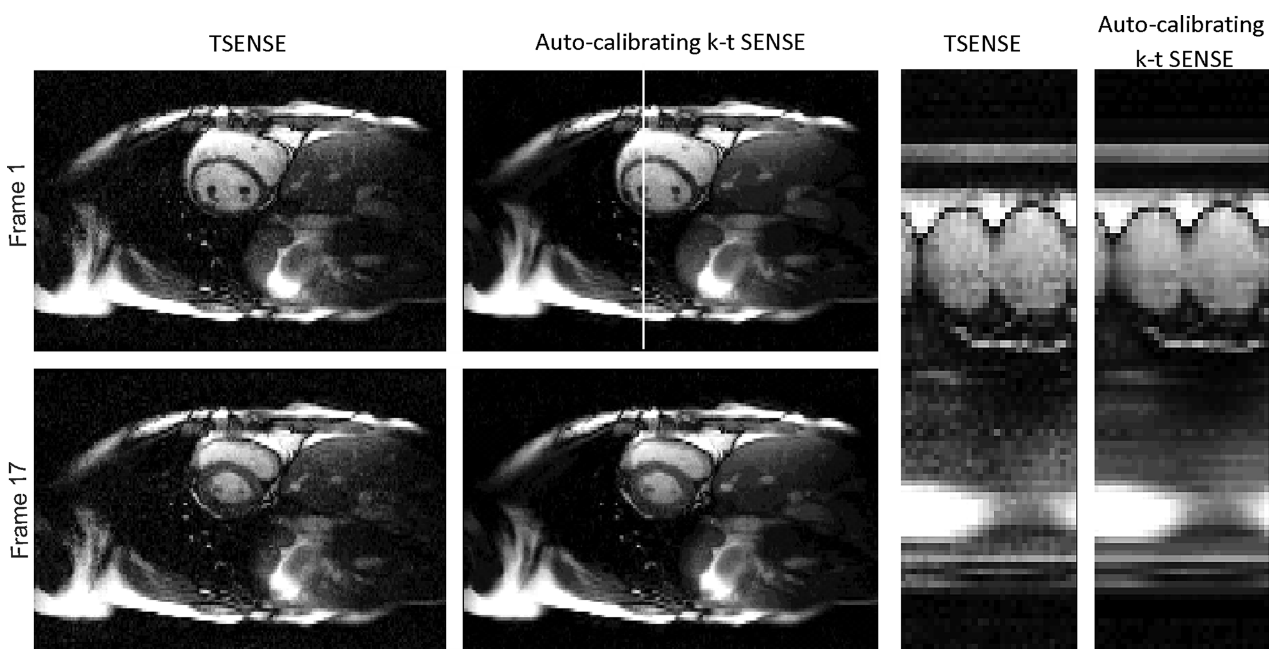

FIG. 5. In vivo free-breathing experiments (acceleration factor $R=4$) without acquisition of training lines: images reconstructed with TSENSE and auto-calibrating k–t SENSE reconstruction. Here, of two stages of the cardiac cycle are shown as well as the m-mode along the white continues line.

It has been shown that in terms of temporal filtering the auto-calibration approach shows the same performance as conventional k–t SENSE with a full-resolution training data set. Compared to conventional k–t SENSE with low resolution training data (e.g. 21 or less training lines) the auto-calibration approach leads to reduced blurring.

The noise level in auto-calibrated k–t SENSE is higher than in the conventional approach. This can be explained by the noise amplification (g-factor) in the TSENSE reconstructed images that are used as training data. The higher noise level in the training data is then transferred to the final reconstructed images. The higher noise level was not a problem in the cardiac cine experiment shown here, but might become problematic at very high acceleration factors. However, it should be noted that the effective acceleration factor is higher than in conventional k–t SENSE because no additional training data have to be acquired.

CONCLUSION

Auto-calibrated k–t SENSE provides high quality reconstructions for dynamic imaging applications. Temporal filtering effects are minimized because a training data set with full spatial and temporal resolution is obtained from the subsampled data itself. Since the acquisition of the training data is not necessary in order to perform the reconstruction, the acquisition time is further reduced.

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