Towards real-time imaging: a literature study on fast imaging by undersampling and smart reconstruction

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Abstract

Magnetic Resonance Imaging (MRI) is a non-invasive imaging modality. Unlike Computed Tomography (CT), MRI does not use ionizing radiation. Over the years, MRI has improved dramatically in both imaging quality and imaging speed. This revolutionized the field of diagnostic medicine. However, imaging speed, which is essential to many of the MRI applications, remains a major challenge. Imaging speed can be improved by faster collection of data. This can be achieved by using sophisticated non-Cartesian k-space trajectories. Popular non-Cartesian schemes include encoding along a radial line or spirals. The point has nearly been reached in which fundamental physical and physiological effects limits the ability to simply encode data more quickly. This fundamental limit has led many researchers to look for methods to reduce the amount of acquired data without degrading image quality. In order to address this issue, various reconstruction techniques have been proposed; in this paper three of them are discussed. Beginning with SENSE(proposed in 1997), followed by k-t BLAST/k-t SENSE, nonlinear inverse reconstruction and ending with a combination of techniques very recently proposed(August 2010). We will also evaluate two of the three above mentioned techniques with one application i.e. cardiac cine imaging.

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Contents

1 Introduction

Magnetic Resonance Imaging (MRI) is an imaging tool widely used in clinical diagnosis of disease processes throughout the body.

Since the conception of MRI by Lauterbur [24], there has been a quest for speed which acted as a major driving force for further clinical, technical and scientific development. In clinical MRI, there has always been a great need to increase imaging speed. Relatively long scanning times in combination with the motion of organs are inducing artifacts in the imaging process, especially around moving organs like the heart.

The desire to visualize physiological processes, such as cardiac cine imaging, at high spatio-temporal resolution, has been a driving force behind the development of real time MRI. Today's fastest imaging sequences and state of the art scanners are continuously approaching certain basic limits on imaging speed. The limits are technical and physiological, which are related to the maximum gradient field switching rate and the pattern how this can be applied to increase speed. This has to do with limitation to what humans can tolerate because extremely fast gradient switching might cause unwanted neuromuscular stimulation and dense radiofrequency pulses can lead to high energy deposits in the body, causing damaging tissue heating[20].

In order to address this issue of damaging heating tissue and neuromuscular stimulation, various reconstruction techniques have been proposed:
The first technique is sensitivity encoding(SENSE, see section 2.1), in which the data is acquired by parallel imaging. This means that the MR signal is acquired with more than one detector (receive coil)simultaneously from different positions and stored separately. The SENSE technique then makes it possible to gain time by reducing the number of repetitions i.e. sampling fewer data per receive coil. Such undersampling, however, leads to aliasing and superimposed pixel values when the inverse Fourier transform is applied. To unfold the image values, the spatial sensitivity profile from each coil is exploited.
The second technique is k-t BLAST/k-t SENSE(see section 2.2), a reconstruction technique which is based on the quasi-periodicity of the imaged content, such as cardiac cine imaging. This approach uses a diagonal form of the covariance matrix obtained from trained data and imposes it as *a prior* information for the acquisition phase.
The third technique is a nonlinear inverse reconstruction technique(see section 2.3). High quality reconstruction is now possible even when sampling densities are much lower than required. An example is compressed sensing(see subsection 2.3.1), where only good reconstruction results are obtained when the image is sparse in an appropriate domain and samples are obtained with an *incoherent basis*.

The contribution of this thesis is describing the three mentioned techniques for rapid imaging, with particular focus on the used sampling pattern (see subsection 1.2), k-space(see subsection 1.1) and the image reconstruction techniques(see partly subsection 1.3).
Two of the three techniques and a combined method are evaluated with one application; cine imaging of the heart. The combined method includes a fast low angle shot (FLASH) gradient-echo imaging sequence, radial encoding(see section 1.1) and a regularized non-linear reconstruction. It is a promising combination of techniques recently described by Uecker et al[24].

1.1 K-space

Early in the development of MRI it was recognized that the time-varying signals could be detected from precessing magnetization following an RF excitation pulse, a short burst radio frequency matching the Larmor frequency of the nuclei of interest. The MR signal generated with the presence of a slice selective gradient is likewise a polyphonic mixture, containing the encoded spatial position and the magnetization strength on those positions in the selected slice. Each MRI method must have a decoding strategy which'unravels'the 'polyphonic mixture'to produce a spatially resolved image. The basic principle consists of collecting the raw data in a space, called k-space during image acquisition. The k-space is filled with applying x- and y gradients, which traces a particular trajectory into a two dimensional space, which is further sampled into k-space. The coordinate in k-space at which a sample is acquired corresponds to the frequencies of the sinusoidal waves that form the basis for the Fourier transform in x and y direction[21].
The most popular trajectory is sampling of the signal along a Cartesian grid, because of the instrumental imperfections of the early MRI systems and the simple reconstruction of an image by the inverse Fourier transformation of Cartesian data. Despite these advantages for a static image, dynamic monitoring of a moving object is better served with different sampling trajectories [24].
One of the targets in real time imaging, which uses moving objects, is to find the gradient waveform that will traverse k-space from one point to another along a specific path and in minimum-time. The reason is that the acquisition time window is limited because of the exponential decay of the magnetization. Non Cartesian trajectories are faster than Cartesian Trajectories, for example radial lines or spiral trajectories (see figure 2). Radial acquisitions are for example less susceptible to motion artifacts and have better image resolution than Cartesian trajectories [5] and can be significantly under sampled [19].This is because each line crosses the centre of k-space and therefore contributes both high spatial frequencies (outer part of k-space) and low spatial frequencies (inner part of k-space). Above that, spirals and radial make efficient use of the gradient system hardware[15]. Most of their efficiency comes from the fact that a relative small number of interleaves are sufficient to cover whole k-space[1].
The x- and y-gradients are used together for phase encoding and frequency encoding.In order to scan a spoke in k-space ,with a certain angle θ a combination of x and y gradients are selected to accomplish this.[17].
Sampling of those trajectories is more complicated, this is done by using non-linear inversion- or gridding reconstruction.

1.2 Resolution vs. Field of view

The k-space sampling density should be conventionally designed to meet the Nyquist criterion. This means that the sample frequency must be at least two times higher than the highest frequency component to be reconstructed from the signal, to avoid aliasing.. This maximum component follows field of view and resolution (see figure 1). The maximum allowed Nyquist sampling periods are given by [6]:

$$\Delta x \leq \frac{1}{2k_R} \quad \text{and} \quad \Delta y \leq \frac{1}{2k_{PE}} \tag{1}$$

Where the minimum of samples required for aliasing-free sampling is directly proportional to the step size. The field of view is determined by the density of sampling of the region of interest. For example a larger object requires denser sampling of k-space than other regions. Accordingly [6]:

$$FOV \equiv \frac{1}{\frac{\gamma}{2\pi} G_R \Delta t} \tag{2}$$

where γ is the gyromagnetic ratio, G_R is the read gradient and Δt is the uniform time intervals. The resolution depends on which part of k-space is sampled (see figure 1). In figure 1b the high frequency region is neglected and set to zero. Therefore, a pulse sequence inherently represents a low-pass filtering process applied to the underlying image. The low-pass filter implied by these methods is a rectangle in Fourier dimensions, they represent the k-space steps in respectively read- and phase encode direction [6]:

$$k_R = \frac{\gamma}{2\pi} G_R \Delta t \tag{3}$$

$$k_{PE} = \frac{\gamma}{2\pi} \Delta G_{PE} \tau_{PE} \tag{4}$$

where τ is the duration of the phase encoding gradient. The MR resolution is given by Fourier resolution, so k-space can be represented by sinc functions. It is sufficient to consider the main lobes of the sinc functions. The Fourier resolution (FWHM) is approximated by taking half of the interval between the first two zeros of the sinc function [6]:

$$FWHM_R = \frac{1}{k_R} \quad \text{and} \quad FWHM_{PE} = \frac{1}{k_{PE}} \tag{5}$$

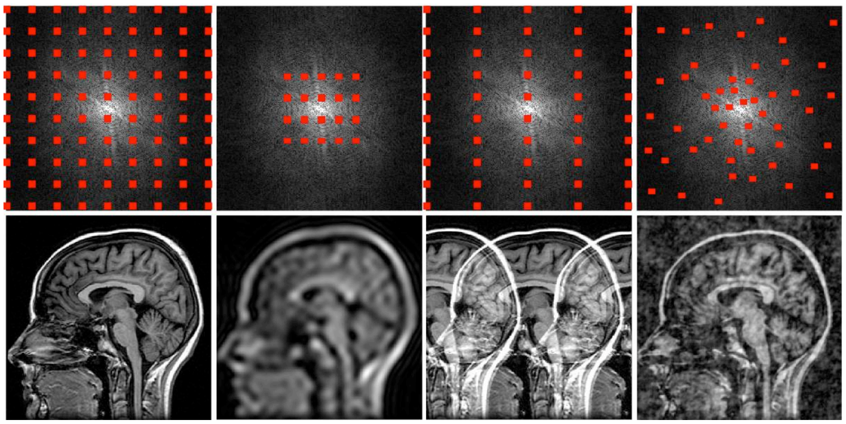

Figure 1: The relation between the sampling pattern in the spatial-frequency domain (k-space) and the image in spatial domain. Image resolution is determined by the extent of the k-space that is covered. The supported field of view is determined by the sampling density. Violation of the Nyquist criteria results in aliasing interference in the image domain. The appearance of the artefact depends on the sampling. Coherent folding is produced by equispaced sampling and incoherent interference is produced by irregular sampling

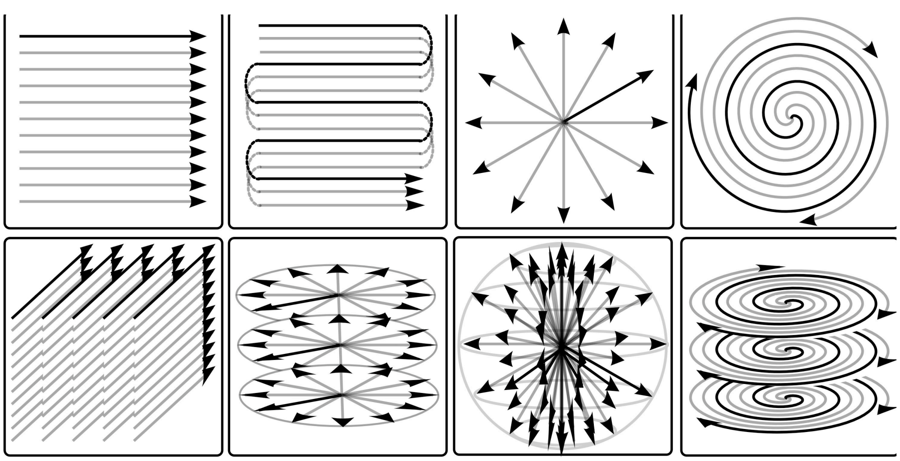

Figure 2: Common sampling trajectories. Top, left to right: Cartesian 2D, Cartesian echo-planar, radial, spiral. Bottom left to right: Cartesian 3D, stack of radial, 3D radial, 3D stack of spirals

1.3 Regularization

Regularization penalizes the complexity of a learning algorithm[10], with some prior knowledge about the observed object. Penalizing implies adding quality weighting factors, which result in a better estimate of the observed object. When the aim is reduction of acquisition time, which is the case in real time imaging, undersampling of k-space would be an option. However, it is well-known that this may cause all sorts of image artifacts , which can be modified by alternative reconstruction methods[23]; such as supervised learning algorithms.
The regularization/optimization problem parameters in real time imaging is: the operator(Ψm). The operator consists of the undersampled Fourier Transform(F_u), the acquired k-space(y), the images themselves represented as vector(m) and the noise level(ϵ). Two examples of regularizations are: l_1 and l_2 regularization. l_1 is given by:

$$\text{minimize} \qquad ||\Psi m||_1 \tag{6}$$

$$\text{s.t.} \quad ||F_u m - y||_1 < \epsilon, \tag{7}$$

where l_2 is given by:

$$\frac{1}{2}||\Psi m||_2^2 \tag{8}$$

It has frequently been observed that l_1 regularization in many models often results in a sparse solution[3, 16], which is an essential aspect of compressed Sensing (see paragraph 2.3.1). On the other hand, l_2 is easier to implement and outperforms l_1 in calculation time. The two mentioned regularization methods are compared in a study of Andrew Y. Ng, a study to the logistic regression performance of regularized learning algorithms.
In one experiment both are tested on data with many irrelevant features[1] and the learning algorithms are trained with 100 examples. The total number of features varies and just a single feature is relevant. Andrew Y. Ng, mathematical expert showed that l_1 performs extremely well in ignoring irrelevant features. Also when the number of relevant features increases, l_1 is superior to l_2 [16]. The bad performance of l_2 is mainly a result of the rotational invariance[16], a characteristic shared by a large class of learning algorithms. However, the performance can be improved by increasing the number of training samples.

2 Methods

2.1 SENSE

Instead of using different trajectories in k-space to increase scan time and reduce motion artifacts, multiple coils can be used as well. By using multiple receiver coils in parallel, scan time in Fourier imaging can be considerably reduced[18]. Each surface coil will sense the signal differently depending on its position. Sensitivity encoding(SENSE) is based on the fact that receiver sensitivity generally has an encoding effect complementary to Fourier preparation by linear field gradients.

Sampling
The SENSE technique reduces scan time by sampling fewer points. The phase encoding is reduced by increasing the distance of readout lines in k-space[18], such that the sample area

[1] Features are the characteristics of the content of your data

remains unchanged. In standard Fourier imaging, reducing the sample density will result in the reduction of the FOV(see equation 2). Increasing the distance in k-space, with a fixed FOV, without reducing the volume that is being imaged, will result in a fold over effect in the image, due to the properties of the IDFT (Inverse Discrete Fourier Transform).

K-space
The next step is to unfold the image. Each pixel which is superimposed must be separated. The key to signal separation lies in the fact that in each single-coil image signal superposition occurs with different weights according to local coil sensitivities[18]. With the weights the superimposed intensities can be rearranged to their original positions as shown in figure 3 .

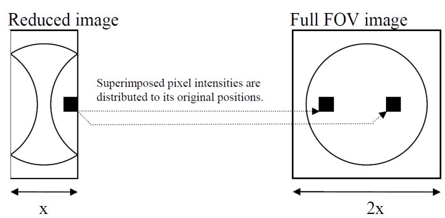

Figure 3: Image folding due to undersampling of k-space. The signal of the two marked spatial subregions in the right full FOV have both contributed to the signal intensity in the left folded image. This intensity should be separated again into its reconstructed origins in the full image FOV

2.2 k-t BLAST and k-t SENSE

In dynamic MRI, a temporal sequence(in time) of spatial MR images (2D or 3D) is constructed(see figure 4, Top). Especially dynamic images depicting a quasi periodic process are highly compressible, such as cardiac image sequences. This has been demonstrated by the success of MPEG, which uses the fact that some parts of the frames stays constant or else undergo motion that is similar between neighbouring pixels. Based on this quasi-periodicity, severe undersampling of k-space is possible. k-t BLAST and k-t SENSE are the techniques to recover the missing data, where SENSE makes use of the coil sensitivities in addition.

Sampling[22]
Sampling of k-space occurs on a regular set of congruent lines, where an undersampled sets of phase encode line are acquired at one out four time points (see figure 5). In this way it is impossible to meet the spatial Nyquist rate (see equation 1), but in time the signal is fully sampled. Sub-Nyquist sampling, followed by linear reconstruction causes coherent aliasing of the signal in the spatial-temporal frequency (x-f)domain(see figure 4, Bottom), which is shifted due the congruent sampling.

K-space[22]
Dynamic MRI data are acquired in the spatial frequency vs. time (k -t) domain, undersampled by a factor four, according to the k-t sampling pattern(see left figure 5). The temporal average is subtracted from the sampled phase encodes(see figure 7, 4.2). Inverse Fourier transform is separately applied to k- and t-domain to yield an x-f array with a lattice structure(see figure 7, 4.3 and 4.5) .

Reconstruction(BLAST)[22]
In essence, K-t blast is the reconstruction of the original data from the aliased data, which is based on two steps: The first step is to make use of prior information, which can be obtained from measured training data. The data is stored in a matrix **M**, which specifies where the changes in spatial and temporal domain are likely to occur(x-f space). The second step is setting all time varying intensity maps equal to each other, which means obtaining the DC estimate. The DC estimate contains information about the present intensities in each time frame, localized in the center of k-space. DC estimate is important to enable normalisation of image intensity.
In the training stage with several steps the diagonal elements of matrix M are obtained. The training set consisted of the densely sampled central region of k-space only, because mainly the central region changes in time.
The below mentioned steps are used to determine Matrix **M**:

1. Filtering along the phase encode direction in k-space of the training data to reduce truncated artifacts(see figure 6, 3.1).
2. On the filtered training set, the inverse Fourier transform to the k-space's is applied to yield a series of low-resolution images (see figure 6, 3.2).
3. The image columns from all time frames are gathered into a x-t array and inverse Fourier transform is applied to t to yield a x-f array (see figure 6, 3.3).
4. The DC term is set to zero(f=0) to normalize all image intensities (see figure 6, 3.4).
5. Filtering along f to reduce noise with high temporal frequencies (see figure 6, 3.5).
6. Multiplying by a safety margin for a better estimate of the intensity magnitude (see figure 6, 3.6).
7. Taking the squared magnitude yielding the estimated deviation from the baseline, which are the diagonal elements of matrix M (see figure 6, 3.7).
   Matrix M represents the changes in spatial and temporal domain.

The following describes about the acquisition stage after Matrix **M** determination:
The sparsely sampled k-t spaces are averaged to yield a temporal average to obtain a time varying intensity average(see figure 7, 4.1). Inverse Fourier transform in k-domain is applied to obtain data in x-t domain(see figure 7, 4.3). Inverse Fourier in time is applied to yield x-f domain. The image column from the x-f domain at $f = 0$ is used to get a DC estimate (see figure 7,4.4),
In other words, the aliasing in x-f array, which is the result of undersampling along a sheared grid pattern is unfolded by the prior determined matrix **M**. The frame by frame intensity variation is resolved by the DC estimate.

Reconstruction(SENSE)[22]
In addition to k-t blast, it is possible to use information from additional receiver coils to resolve the aliasing. Specifically, by incorporating the sensitivity information, generalized in the sensitivity matrix. For k-t SENSE, the data from each coil are arranged in a separate k-t array. The reconstruction method of k-t blast(**M**) extended with the sensitivity matrix will be used to effectively resolve the aliasing

It should be noted that reconstruction is considerably more demanding if the k-t sampling does not conform the lattice structure.

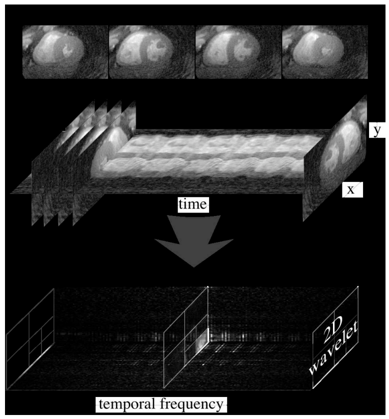

Figure 4: Top: Dynamic MRI yields a temporal sequence of multiple spatial MR images (2D or 3D) Bottom: Dynamic images have a sparse representation in an appropriate transform domain.

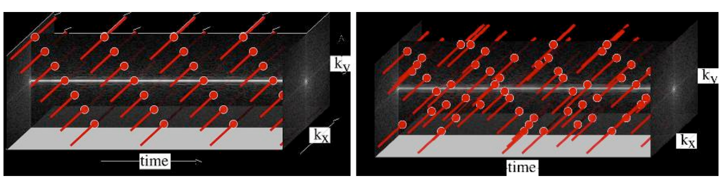

Figure 5: Traditional k-t sequential sampling and random sampling

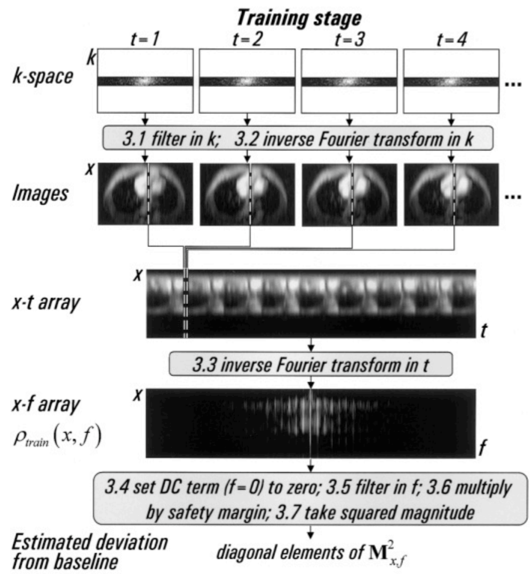

Figure 6: Main processing steps for the training stage of k-t BLAST

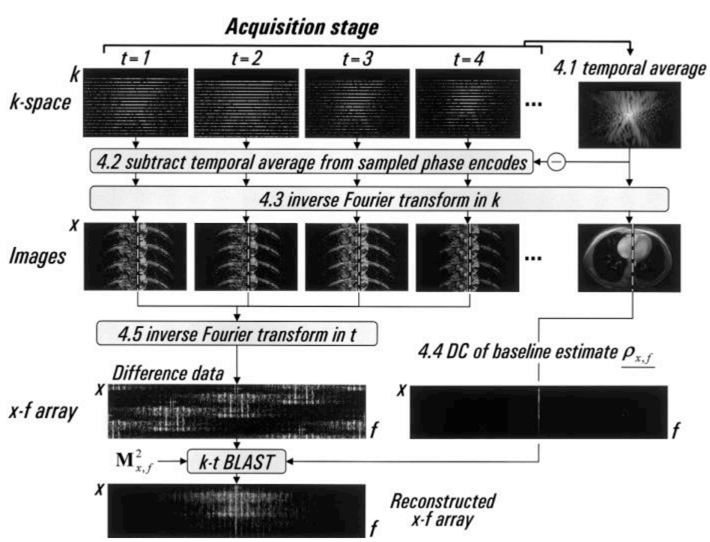

Figure 7: Main processing steps for the acquisition stage of k-t BLAST/ k-t Sense

2.3 Nonlinear reconstruction techniques

It is a method to deal with undersampling of k-space when using alternatively k-space trajectories to increase imaging speeds.
When Nyquist is violated, either field of view(FOV) becomes smaller(see equation 2) or all kinds of image artifacts occur. This can be modified by using alternative reconstruction methods[23], such as supervised learning algorithms. In this section we present an iterative reconstruction method for undersampled radial MRI which is based on: (i) a nonlinear optimization, (ii) by combining the acquired signal from multiple coils and (iii) by incorporation of prior knowledge, implemented by penalty functions[2].

Sampling and K-space
The acquisition of k-space can be done in many different trajectories (1.1) and the optimal choice depends on: (i) the imaged process, (ii) the purpose of the scan (iii) and the other acquisition parameters. Radial sampling has two attractive characteristics: each line crosses the center of k-space and therefore contributes to high spatial and low spatial frequencies[24] and it has low sensitivity for object motion.
An important characteristic of radial sampling is folding artifacts due to aliasing, which have a very different appearance compared to the central image content. For this reason it is possible to remove these so-called streaking artifacts during the reconstruction phase with the use of prior information about the structure of the image. For radial MRI, this has been demonstrated by using an iterative image reconstruction method with the penalization of the total variation(TV) of the image[2]. Another important difference from existing reconstruction methods is that for radial trajectories a much lower number of spikes are needed than data samples per spoke.

Reconstruction MRI acquisitions using radial trajectories are commonly reconstructed with either projection reconstruction or regridding methods but these methods lead mostly to a low temporal resolution or a poor spatial resolution(streaking artifacts).To overcome the problems of undersampled radial encoded lines is to see it as an inverse problem; as described in the section 1.3 Regularization. The inverse problem parameters are: (i) the undersample Fourier Transform, (ii) the acquired k-space, (iii) the images themselves and (iv) the noise level. By optimizing this problem, the best image fit of the measured data can be found. Finding a solution requires a highly efficient optimization method due to the large size of the parameter space. A suitable approach for such problems is the conjugate gradient method. The conjugate gradient is an iterative two-step scheme, which is repeated until a satisfying solution has been found. (See Figure 8)
From experiments it has been observed that reconstruction of the undersampled radial images with Eq. (6), still leads to streaking artifacts[2]. One of the reasons why reconstruction fails, is that solution space is too large. By using some prior knowledge about the true object, this space can be restricted. This requires extension of Eq.(6) with quality weighting/ penalty terms, which result in:

$$\frac{1}{2}||\Psi m||_2^2 + \sum_i \lambda_i R_i \tag{9}$$

where R_i contains the penalty functions. The coefficients λ_i represent the tuning factors for shifting the preference from matching the image to the measured data, according to the prior knowledge.

In radial MRI there are several choices to restrict solution space: penalize image intensities outside FOV, suppression of negative values and restriction of total variance(TV). TV is based on the fact that the true object and aliasing effects have a different appearance.

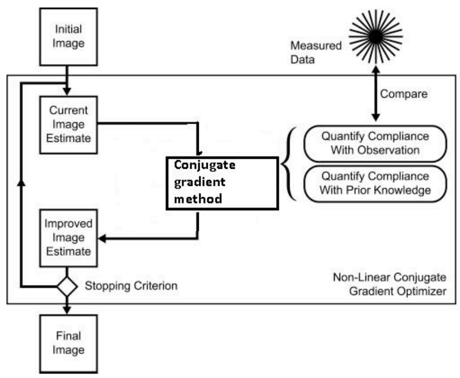

Figure 8: Schematic diagram of the proposed iterative reconstruction technique. The procedure has been formulated as an inverse problem. The solution employs a nonlinear conjugate gradient method to obtain an image estimate that complies with the measured data as well as prior knowledge.

2.3.1 Compressed Sensing

In CS, a relatively small number of 'random' linear combination of the signal values is measured, which implies that it is an undersampled signal. The underlying signal is compressible, because the nominal signal sampling(Nyquist criterium) is a gross overestimate of the effective number of 'degrees of freedom' of the signal. As a result, the signal can be reconstructed using a non linear reconstruction(l_1 regularization) technique.

Sampling
Compressed sensing is based on the premise that raw data in dynamic imaging exhibit correlations in k-space and in time[13], allowing to reconstruct the image with a reduced amount of data, without compromising the spatiotemporal resolution. Compressed Sense uses the property of sparsity of images. Each image is more or less sparse than others. So if the underlying image exhibits transform sparsity and if k-space under sampling results in incoherent artifacts in the transform domain, then the image can be recovered from randomly under sampled frequency domain data, provided an appropriate nonlinear recovery scheme is used. Thus the aim is to design a practical sampling scheme that exploits the interference properties, in the frequency domain. No interference means that there is no strict relation between measurements. A sampling method must be designed to guarantee this. In Sparse MRI[12] different sample schemes are compared with the Transform Point Spread Function(TPSF) analysis, which quantifies the interference of measurements. Comparison of different Fourier analysis shows that the peak interference is significantly reduced by using a 3 dimensional Fourier transform [11](which is good, because the need for speed is highest in 3D imaging). 3D imaging is more attractive because the spatial resolution is the in all direction(isotropic voxels)

and it will leads to higher SNR. But sources of artifacts present during scanning will affect all slices in a 3D scan[21].

K-space
CS is characterized by incoherent measurements.The optimal gradient waveform to obtain this is the spiral trajectory, follows the TPSF[11](see figure 2).

Reconstruction(Regularization)
In compressed sensing the objective is to get a sparse solution, where l_1 leads to a sparse solution and l_2 penalizes large coefficients heavily. In compressed sensing the small coefficients must be penalized, not the large. In l_1, many small coefficients tend to carry a large penalty than a few large coefficients, therefore small coefficients are suppressed and solutions are often sparse[4]. So both regularization methods do not lead to the same level of sparseness, because l_1 drives many coefficients to zero.

3 Accelerating Cardiac Cine 3D Imaging using *k-t* BLAST, Compressed Sensing and "Real time MRI at a resolution of 20ms"

An application of real time imaging technique is to make cine acquisitions of the moving heart. A real time cine acquisition of the heart makes it possible to directly monitor the contracting heart and the resulting blood flow. It could help by the diagnosis of typical heart failures such as myocardial insufficiency. Here we discuss three methods: k-t BLAST[10], Compressed Sensing[14] and "Real time MRI at a resolution of 20ms".

3.1 K-t BLAST

In general, each new application of k-t BLAST requires careful considerations, since the distribution in K-T BLAST depends on how the image content is distributed in x-f space. However, the high degree of correlation in both space and time makes cardiac cine imaging very suitable for this method.
The key challenge is that the k-t concept is applied to the pseudo-time axis which refers to cardiac phase acquisition with cardiac gating rather than real time imaging.
In practice,the subject must hold his/her breath when the acquisition of multiple frames is started. A potential problem can be misregistration of the frames, between the phases of acquisition.
Two solutions are given by Kozerke et al.[10] to deal with this problem: single breath hold sampling and using multiple receiver coils to reduce scan time.
The single breath hold sample strategy implies interleaved acquisition of the low resolution training data, which enables the acquisition of data in a single scan. With the low resolution training data, an estimate of the expected signal in x-f space is obtained. The clinical usefulness of this technique is questionable because it requires long breath-holds(25-27 sec.), which may be challenging for patients. However, the breath-hold time could be reduced by using k-t SENSE, but this is not yet investigated.
In all subjects, the reconstructed images were artifacts-free. Also good consistence of acquisitions between the frames were found(Root mean square error was low). Also by using the scanner implementation for single breath hold sampling as described by Kozerke et al.[10] it

was possible to acquire data sets of the heart at high spatial resolution($2 * 2 * 5mm^3$) with a temporal resolution of 33 ms in a single breathhold lasting 21 seconds. The acquisition strategy was well tolerated by healthy subjects and patients In all subjects, the reconstructed images were artifacts-free. Also good consistence of acquisitions between the phases are found(Root mean square error is low). The breath-hold time could be reduced by using k-t SENSE, but this is not yet investigated. By using the scanner implementation described by Kozerke et al.[10] it was possible to acquire volumetric data sets of the heart at high spatial resolution($2 * 2 * 5mm^3$) with a temporal resolution of 33 ms.

3.2 Compressed Sensing

CS is suitable for making a cine acquisition of the moving heart. Dynamic imaging requires high spatial - and temporal resolution which encourages undersampling. CS is ideal for resolving the undersampled artifacts.Using the method described by Lustig et al.[12] it was possible to acquire data sets of the heart at high spatial resolution($2.5 * 2.5 * 2.5mm^3$) with a temporal resolution of 40 ms[14]. The challenges of making a cine acquisition of the heart are nearly the same as in k-t BLAST. The sampling pattern of k-t BLAST can also be used here,because it results in a sparse solution. The only problem of sampling along a congruent line is getting too much interference in the measured signal. The solution is a random order in the acquisition of k-space lines in time (see right figure 5).
The clinical usefulness of CS is however still questionable because of long computation time and the reconstruction quality in terms of clinical significance which are two of the main problems.

3.3 "Real time MRI at a resolution of 20ms"

In an article of Uecker et al. a method is presented to reduce the temporal resolution to 30ms of the moving heart[24]. The real-time method combines the following: (i) FLASH MRI, (ii) a radial encoding scheme and (iii) an iterative nonlinear reconstruction method.
FLASH is based on the application of reduced flip angles: for excitation, the acquisition of magnetic field gradient echoes and considerably shortened repetition times[7].
Radial encoding is used to increase imaging speed and is suitable for organs showing quasi-periodicity processes such as the heart.Radial k-space sampling is preferred above spiral sampling, because radial sampling results in fewer motion artifacts and improved heart wall definition compared to spiral k-space sampling[9]. Each single turn corresponds to a full image and contains only 15 radial spokes distributed over a full 360 degrees circle in order to homogenously sample the k-space. The chronological order of the acquired spokes was chosen to be sequential in each turn.
Reconstruction of the undersampled data was performed by an iterative nonlinear reconstruction method with l_2 regularization.
For the heart the combined method performed without synchronization with the electrocardiogram and without breathholds. This is not only beneficial for the patients but also expected to improve the diagnostic quality of the examination by eliminating motion artifacts and temporal blurring in cine reconstruction for multiple heart beats. Using the implementation by Uecker et al. [24] a high spatial resolution ($2 * 2 * 8mm^3$) with a temporal resolution of 30 ms is reached. Drawback of this combined method is the computation time.

4 Discussion and Conclusion

I have presented briefly the theory of SENSE, k-t BLAST/k-t SENSE, Nonlinear reconstruction and Compressed Sensing. On examining each of the techniques, the following findings came up for discussion. SENSE technique requires multiple coils for undersampling and time consuming because of the long numerical calculation times which is a disadvantage. K-t BLAST uses prior information to be used and needs high degree of correlation in both space and time. K-t sense needs to be completely investigated so as to be used in real time. Nonlinear reconstruction techniques require prior knowledge about the object of to restrict solution space. The object of interest can be for example cardiac cine imaging. Compressed sensing which is an example of a non-linear reconstruction technique has a similar disadvantage
A rather new method wherein different existing techniques are combined is also discussed here[24]. It was evaluated with one object of interest i.e., cardiac cine imaging, where also the performance of other different approaches discussed here are evaluated.
It is seen that combining different techniques (FLASH MRI, a radial encoding scheme and an iterative nonlinear reconstruction method), as described by Uecker et al.[24], is the most promising real time imaging approach that we see today. It's because of the high spatial resolution, temporal resolution and mainly least burdensome for patients because they do not need to hold their breath at all in contrast to the other techniques. In comparison with MRI reconstructions based on compressed sensing, this approach does not require sparsity and therefore reduces the complexity of the minimization problem. The combined techniques does not depend on the specific nature of K-t space, as required, for example, for UNFOLD(unalisaing by Fourier-encoding the overlaps using the temporal dimension) and TSENSE(adaptive sensitivity encoding incorporating temporal filtering), which is also required for K-t BLAST/SENSE. A drawback of combined techniques is however the long computation time.
On the other hand, it's needed that the techniques like CS for rapid imaging, different sampling trajectories and reconstruction algorithms are needed to speed up the acquisition of the frames. This is due to the hardware limitations and the different types of reconstruction methods used.
Even though the k-t BLAST/SENSE and the compressed sensing approach appear drastically different, a close look at the algorithms however reveals the striking similarities[8]. It was seen from Jung et al. that the diagonal signal covariance matrix in k-t BLAST/SENSE was originally designed to obtain a sparse solution by successively solving quadratic optimization problems.
This doesn't mean that other techniques as described in the thesis are amortized. Compressed Sensing is for example still in its infancy. Many crucial issues remain unsettled, but the potency is there. If theoretical and practical research problems in CS are solved, it can be considered as a potential technique.

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