Approaches for Image Reconstruction in Low-Field Magnetic Resonance Imaging

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Abstract

Background: Magnetic Resonance Imaging (MRI) and spectroscopic techniques are frequently employed for clinical diagnostics as well as basic research in areas like cognitive neuroimaging. MRI is a widely used imaging modality for intracranial diseases. However, conventional MRI is expensive to purchase, maintain and sustain, limiting their use in low-income countries. Low field MRI can provide an economical, long-term, and safe imaging option to high-field MRI and computed tomography (CT) for brain imaging. This paper offers a review of the image reconstruction techniques used in low field magnetic resonance imaging (MRI). It is aimed at familiarizing the readers with the relevant knowledge, literature, and the latest updates on the state-of-art image reconstruction techniques that have been used in low field MRI citing their strengths, and areas for improvement.

Methods: An in-depth keyword-based search was undertaken for publications on image reconstruction approaches in low-field MRI in the top scientific databases such as Google Scholar, Wiley, Science Direct, Springer, IEEE, Scopus, Nature, Elsevier, and PubMed throughout this study. This research also contained relevant postgraduate theses. For the selection of relevant research publications, the PRISMA flow diagram and protocol were also used.

Results: Studies revealed that Inhomogeneities are present in low field MRI, implying that the traditional method of acquiring the image, using the inverse Fourier Transform, is no longer viable. The image reconstruction techniques reviewed include iterative methods, dictionary learning methods, and deep learning methods. Experimental results from the literature revealed improved image quality of the reconstructed images using data driven and learning based methods (deep learning and dictionary learning methods).

Conclusion: The study revealed that there is limited literature on the image reconstruction approaches in low field MRI even if though there are sufficient studies on the subject in high field MRI. Data driven and learning based methods improves image reconstruction quality when compared to analytic and iterative approaches.

1. Background

In humans, magnetic resonance imaging (MRI) and spectroscopic techniques are frequently employed for clinical diagnostics [1] as well as basic research in areas like cognitive neuroimaging [2]. Also, MRI is a widely used imaging modality for intracranial diseases. MRI technology is used in medicine to visualize the structure of human anatomy in a noninvasive and nonionizing way [3] [4] [5] [6] [7]. The following are the classifications of MRI systems based on the strength of the magnetic field they produce (in Tesla): Ultra-high field > 3T, high field (1−3T), middle (0.5−1T), low field (0.1−0.5T), and ultra-low field (<0.1−0.1T) [8] [9]. Traditional MRI scanners, on the other hand, are costly to purchase and maintain, limiting their use in low-income countries [8]. In developing countries, low-field MRI equipment can provide an economical, long-term, and safe imaging option to high-field MRI and computed tomography (CT) for

brain imaging [8]. Moreover, Hömmen et al. [10] revealed that existing ultra low-field MRI systems can produce a sufficient signal-to-noise ratio (SNR) required for clinical imaging. Huang et al. [11] revealed that portable low-cost MRI systems can provide a point of care and timely MRI diagnosis especially to low-income countries where there are less than 0.1 MRI scans per 1,000,000 people [12] [13]. Several studies [8], [14] have indicated that low-field MRI scanners have a low signal-to-noise ratio (SNR), resulting in noisy images. This was supported by Hömmen et al. [10] that found out that image artifacts influence the reconstruction quality.

1.1 Image Enhancement

Humans employ their five senses to comprehend their surroundings (sight, hearing, touch, smell, and taste). The most powerful of the five senses is sight. Receiving and evaluating images accounts for the majority of human cerebral activity, with image processing accounting for more than 99% of all brain activity [15]. Images are not self-explanatory; instead, interpreting them takes professional competence, which must evolve in tandem with the growing variety of imaging techniques. Image enhancement is a technique for improving the quality of medical images so that they can be viewed and interpreted more readily. Image enhancement is a subjective field of image processing in which the best method is determined by human perception based on the produced results. The goal of image enhancement is to bring out hidden detail or highlight only the features of interest in an image. This is usually done by increasing the contrast so that the enhanced image can look better than the original [16].

Low magnetic fields (particularly in low field MRI) are the conditions that cause image quality to deteriorate during imaging. Several solutions have been offered to remedy the problem of image quality degradations, including sharpening, deburring, noise reduction, and contrast enhancement, among others [17]. Contrast enhancement is a technique used by researchers to increase the quality of images. Image enhancement techniques are a group of approaches that aim to improve the visual look of an image or transform it into a format that is better suitable for human or computer analysis [18]. Enhancement procedures are used to reduce image noise and increase the contrast of features of interest. When noise levels are high, it might be difficult to evaluate images where the contrast between normal and sick tissue is fine. In many cases, image enhancement improves image quality and makes diagnosis easier. Enhancement techniques are commonly used to make images more sharp for human observers, but they can also be used as a pre-processing step for automated analysis. Image enhancement techniques are mathematical strategies for enhancing the quality of an image. The result is a new image that, in certain ways, shows some features better than they appeared in the original image. Multiple processed copies of the original image can also be obtained or computed, each highlighting a distinct characteristic. If applied incorrectly, enhancement techniques can increase noise while increasing contrast, lose tiny details and edge sharpness while removing noise, and produce errors in general. To achieve the finest possible augmented image, users must be mindful of these hazards. Enhancement of specific aspects in photographs is frequently accompanied by unfavorable effects. It's possible that crucial image data has been lost, or that the upgraded image is a poor representation of the original.

Furthermore, it is unrealistic to expect enhancement techniques to supply information not present in the original image. Noise or other unpleasant image components may be increased without the user's knowledge if the image does not include the characteristic to be enhanced. However, image enhancement can have unintended consequences, such as the loss of important information or a poor depiction of the original image. However, some image enhancement techniques cause problems such as noise creation, over-enhancing, feature loss, brightness, and darkening [17]. Furthermore, image enhancement characteristics do not convey information that is not present in the original image if a given feature to be enhanced is not present in the original image [19].

There are two types of image enhancement: spatial domain and frequency domain. The image plane is referred to as the spatial domain, and techniques in this area are focused on directly manipulating pixels in an image. Frequency domain processing approaches work by altering an image's Fourier transform. It's not uncommon to see enhancement strategies that combine procedures from these two categories [21]. Procedures that work directly on the pixels that make up the image are known as spatial domain approaches. The expression in equation (1) is used for spatial domain processes:

$$g(x, y) = T[f(x, y)], \qquad (1)$$

where f(x,y) denotes the input image, g(x,y) is the processed image, and T denotes an operator on f defined across a range of values (x, y). T can also conduct operations on a group of images, such as pixel-by-pixel summation of K images for noise reduction [16]. Each location (x, y) receives the operator T, which produces the output $g(x, y)$ at that position. Only the pixels in the area of the image encompassed by the neighbourhood are used in the process. Image reconstruction is one of the techniques used in image enhancement.

1.2 Image Reconstruction

The technique of producing an image from a series of measurements using a computer approach is known as image reconstruction. Most imaging systems in scientific or medical applications use image reconstruction to create image [20]. In MRI, the image reconstruction approach uses k-space data. All of the information needed to reconstruct an image is contained in K-space data, as well as a thorough understanding and classification of the reconstruction method and imaging properties [21]. In k-space data, low-frequency signals are placed in the center of the recorded data, and these low-frequency signals carry contrast information, whilst high-frequency signals are scattered around the center, and these high-frequency signals include spatial resolution or sharpness information. The field of image reconstruction is undergoing a paradigm shift right now. Transform-based or optimization-based techniques have typically dominated image reconstruction. Data-driven machine learning methods, notably deep learning and dictionary learning, have a considerable advantage over earlier methods for image reconstruction, according to recent study.

1.3 Research Objectives and Outline

It is vital to do a systematic review of the image reconstruction approaches utilized in low-field MRI, as a result of recent breakthroughs and numerous influential works in the field. The purpose of this study is to provide readers with important knowledge, literature, and the most recent updates on state-of-the-art image reconstruction techniques that have been employed in low field MRI, as well as their objectives, outcomes, and areas for improvement. The research was limited to the use of image reconstruction techniques in low-field MRI; high-field MRI was not included in the study.

The rest of the article is organized as follows. In section 2, the methodology is discussed; section 2.1 discusses the identification of the Articles for Review; section 2.2 discusses inclusion criteria, and section 2.3 discusses exclusion criteria. In section 3, results are discussed, section 3.1 discusses the motivation for use of low field MRI, 3.2 discusses the need for image reconstruction in low field MRI, and 3.3 discusses the image reconstruction techniques in low field MRI, and discussion and conclusions are given in section 4.

2. Methods

2.1 Identification of the Articles for Review

Several review studies argue that reviewing publications from high-quality data sources is critical [22], [23], and [24]. An in-depth keyword-based search was undertaken for publications on image reconstruction approaches in low-field MRI in the top scientific databases such as Google Scholar, Wiley, Science Direct, Springer, IEEE, Scopus, Nature, Elsevier, and PubMed throughout this study. This research also contained relevant postgraduate theses.

2.2 Inclusion criteria

Studies that presented image reconstruction approaches in low-field MRI were considered during this study. For the selection of relevant research publications, the PRISMA flow diagram and protocol [25] were also used. This method consists of four steps: (i) the identification phase, which entailed gathering articles from diverse sources; (ii) the screening procedure. During this phase, duplicate articles were eliminated, as well as ones that were insufficient. (iii) Phase of Eligibility We looked at articles to see if they were eligible for additional review. Articles that were deemed ineligible were omitted. (iv) The included phase is the final phase. During this phase, the articles that were included in the study were analyzed.

2.3 Exclusion criteria

This analysis excludes studies that used image reconstruction techniques in conventional (high field) MRI. Articles involving image reconstruction techniques in other imaging modalities, such as computed tomography, ultrasound imaging, and others, were also eliminated.

3. Results

3.1 Image Reconstruction Approaches in Medical Imaging

Wang et al. [26] suggest in their special issue that the field of medical image reconstruction has progressed through three stages, which include the following:

i. In the first phase, analytical procedures that used an idealized mathematical model of an imaging system, such as the inverse Fourier transform in MRI and the filtered back-projection method (FBP) in computed tomography (CT), were used. These image reconstruction techniques are simple to implement. However, they simply consider the imaging system's sampling properties, with little (if any) regard for the properties of the thing being scanned.

ii. Iterative techniques are used to reconstruct images in the second phase. These methods take into account the statistical and physical characteristics of the imaging system. Most of these methods rely on statistical object models like Markov random fields or regularization techniques like roughness penalties. These techniques have been used commercially in major imaging modalities such as MRI, positron emission tomography, and single-photon emission computed tomography.

iii. The third phase, which has just begun, is the application of data-driven and learning-based image reconstruction approaches. Dictionary learning and machine learning algorithms are employed in tomographic image reconstruction. One of the issues with using these approaches in image reconstruction is a lack of medical imaging data for training and testing due to personal, legal, and business constraints.

The Table 1 below summarizes the current approaches that are used for image reconstruction in medical imaging.

Table 1: Summary of the techniques used in Medical Image Reconstruction

Phase	Techniques Used	Strength	Limitations
First phase	Analytical methods	They are efficient	It requires proper sampling.
Second phase	Iterative methods	The imaging device's statistical and physical features are taken into account.	Disparities between the model and the physical environment.
Third phase	Learning-based methods	Learned signal models can be used to rebuild images from low-quality data.	They are inefficient in terms of computing and necessitate enormous amounts of training data.

3.2 The motivation for use of Low Field MRI

The build-up of cerebrospinal fluid in the cavities of the brain is known as hydrocephalus. If left untreated, it can be lethal. Every year, around 200,000 new instances of hydrocephalus are diagnosed in Sub-Saharan Africa [27]. Magnetic resonance imaging (MRI) is the primary approach for diagnosing hydrocephalus [28]. Many children with hydrocephalus in East Africa and other developing countries now lack access to conventional (high-field) MRI scanners, which are the recommended imaging technique for disease administration and treatment. Traditional MRI scanners are costly to purchase and maintain, which limits their use in low-income nations. In developing nations, low-field MRI equipment can provide an economical [29], long-term, and safe imaging alternative to high-field MRI [30] and computed tomography (CT) for hydrocephalus brain imaging [8]. Low field MRI has also long been regarded to be a technique to give patients with claustrophobia open access [31]. Mbarara University of Science and Technology (MUST) in Uganda is working on a low-field MRI system for hydrocephalus diagnosis with Leiden University Medical Center (LUMC) in the Netherlands, Pennsylvania State University (PSU) in the United States, and the Delft University of Technology (TU Delft) in the Netherlands (Figure 1 shows the low field MRI systems under development). Due to their low cost, portability, and compatibility with patients who have metallic implants, low-field portable MRI scanners, as opposed to conventional MRI scanners based on superconducting magnets, may provide a supplementary medical imaging solution in a moving environment (e.g., the ambulance, the field hospital), rural areas, or developing countries [11]. For details of the low-field MRI under development,   refer to [28], [8], [32], [33]. More so, low field MRI have been used in the diagnosis of other diseases like cerebral malaria [34], imaging of knee injuries [35], diagnosing lesions of the rotator cuff, low field cardiac MRI [36], probing rock pore space using low field nuclear magnetic resonance technologies [37], musculoskeletal conditions [38], tibial component migration [39], low-field dental MRI [40], glioma surgery [41] and glenoid labrum (Shoulder pathology) [42].

3.3 The need for image reconstruction in low field MRI

The strength and uniformity of the magnetic field ensure the quality of the images produced by typical MRI scanners. MRI scanners, on the other hand, are large and expensive since superconducting magnets are required to generate such a field, rendering them inaccessible to a large number of people in underdeveloped countries. The low-cost, portable, and low-field MRI scanners in development do not employ superconducting magnets. The signal-to-noise ratio in these scanners is much poorer due to the reduced magnetic field strength [43]. There are also inhomogeneities, meaning that the usual way of getting the image, based on the inverse Fourier Transform, is no longer practicable [44] [45]. low-field MRI scanners yield noisy images that require enhancement before being used by clinicians in their diagnosis tasks [10] [14] [46] [47] [48] [49] [50]. Figure 2 shows some of the images from our low-field MRI prototypes. As a result, image reconstruction approaches suited for improving image quality in low field MRI are required.

3.4 Approaches for Medical Image Reconstruction in MRI

3.4.1 Medical Image Reconstruction using Fourier Transform Techniques

Several traditional approaches are utilized in MRI image reconstruction. Among these methods include the use of discrete Fourier transforms (DFT), Radon transforms, and parametric procedures. To obtain the required images, the DFT method employs Fourier series on linearly or radially sampled k-space data, the Radon transform employs projection on k-space data, and the parametric technique, also known as a non-Fourier series, employs implicit or explicit data extrapolation to recover some of the unmeasured high-spatial-frequency data [21]. The DFT technique is employed in MR image reconstruction because of the discrete samples included in k-space. A mathematical series with the same number of terms as data samples is defined as the discrete Fourier transform and its inverse. The terms in the series are combined together to calculate one pixel of an MR image. The fast Fourier transform (FFT) is an efficient method for computing a DFT. The inverse discrete Fourier transform (IDFT) approach is used in MRI and is implemented as an inverse Fourier transform (IFT) from uniformly sampled k-space data. The mathematical concept of DFT is well explained in the study by Aibinu et al. [21]. 2D-DFT and inverse 2D-DFT are represented by the equations (2) and (3), respectively. The 2D Fourier transform is produced by doing a Fourier transform on one dimension of the data, then a Fourier transform on the other, while the 2D inverse Fourier transform is acquired by performing simply the inverse Fourier transform on both dimensions of the data.

$$F(u, v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi\left(\frac{ux}{M} + \frac{vy}{N}\right)} \qquad (2)$$

$$f(x, y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u,v) e^{j2\pi\left(\frac{ux}{M} + \frac{vy}{N}\right)} \qquad (3)$$

The implementation of inverse Fourier transform (IFT) in MRI image reconstruction is done in two steps (i) the one-dimensional inverse Fourier transform (1D-IFT) of the row data is computed (ii) followed by the 1D-IFT of the column data. When a 1D-IFT of the k-space column data is computed first, followed by a 1D-IFT of the k-space row data, the same result is produced. Because of the DFT's linear and separability features, the above operation is conceivable. This method of image MRI reconstruction is simple to use, however it has drawbacks such as Gibb's effect at edges, artifacts, and a loss of spatial resolution [21].

3.4.2 Medical Image Reconstruction using Data-Driven Methods

Machine learning, in particular Deep learning, computer vision, and image analysis, work with existing images to produce features, whereas tomographic image reconstruction uses measurement data to produce images of internal structures, which are various features of the underlying images. Machine learning, particularly Deep Learning, is an emerging approach for image reconstruction, as evidenced by the literature, and academics are actively developing Deep Learning-based image reconstruction approaches for a variety of imaging modalities [26]. Also, during medical image reconstruction, adaptive dictionary learning, a particular technique within machine learning, employs learnt iterative techniques. As a result, both Deep Learning and adaptive dictionary learning fall under the category of data-driven image reconstruction approaches, which are the current state-of-the-art in medical image reconstruction. The following parts (a and b) address the dictionary learning and Deep Learning approaches to image reconstruction, respectively.

(a) Dictionary Learning Approach for Medical Image Reconstruction

Dictionary learning (DL) is a representation learning method that aims to find a sparse representation of input data (also known as sparse coding) in the form of a linear combination of basic components [52]. Represent learning is a collection of machine learning techniques that allow a system to automatically identify the representations required for feature identification or classification from raw data. The most typical application of dictionary learning is in compressed sensing. Compressed sensing is a signal processing approach for acquiring and reconstructing a signal that works by finding solutions to underdetermined linear equations. Compressed sensing allows a high-dimensional signal to be reconstructed with only a few linear measurements if the signal is sparse or nearly sparse. The basic

issue is that not all signals match this condition for sparsity. To discover the sparse representation of the signal, some methods can be utilized, such as the wavelet transform or the directional gradient of a rasterized matrix. Various signal recovery techniques, such as basis pursuit, compressive sampling matching pursuit (CoSaMP), and quick non-iterative algorithms, can be used once the signal's matrix or high-dimensional vector has been transferred to a sparse space [52]. The assumption behind dictionary learning is that the dictionary must be inferred from the incoming data. With DL, input signals can be represented with the fewest number of components possible. Dictionary learning is used in signal processing and machine learning to find a frame called a dictionary in which the training data allows for a sparse presentation. There are two current dictionaries design trends: (i) Analytic dictionaries, such as curvelets, contourlets, and bandelets, rely on a mathematical model of the data to construct a dictionary and are characterized by efficient mechanisms for computing transform coefficients as well as robust theoretical guarantees for signal approximation. (ii) Data-Driven Adaptive Dictionaries, which derive an ideal representation from signal observed instances. Because no single dictionary is perfect for all types of signals, adaptive dictionaries are more powerful, but at the cost of increased processing complexity and diminished theoretical assurances [53]. Dictionary learning has been utilized in image processing applications including as image reconstruction, denoising, super-resolution, and segmentation [53].

(b) Deep Learning Technique for Medical Image Reconstruction

After a deep learning-based technique triumphed a computer vision competition in 2012, deep learning (DL) gained prominence [54]. More crucially, deep-learning algorithms have improved their performance since 2010, with DL surpassing human accuracy in large-scale visual identification tests by 2015 [55]. DL varies from traditional machine learning techniques in that it learns picture data without the requirement for feature extraction, whereas previous methods required human involvement [54][56]. DL techniques are based on artificial neural networks (ANNs) [56]. As stated in the introduction, the purpose of this paper is to offer an overview of current approaches for image reconstruction in low field MRI. A more general summary of Deep Learning can be found in the studies [54][55][56][25][57][58][59]. There is a tiny corpus of literature on deep-learning applications in medical image reconstruction. According to the researchers, machine learning has been successfully used to image processing tasks such as segmentation, classification, edge detection, and super-resolution, and they believe it can also be useful for medical image reconstruction. Research on the use of Deep Learning in medical imaging may be found in [60][61][62][63][64][65][66][67].

Deep learning techniques, particularly convolutional neural networks (CNN), have been used in medical imaging modalities such as Magnetic Resonance Imaging. The frequency domain, commonly known as k-space, is utilized to reconstruct images in MRI. All of the information needed to reconstruct an image is contained in K-space data, as well as a thorough understanding and classification of the reconstruction method and imaging properties [21]. The k-center, space's group low-frequency signals, and these low-frequency signals comprise contrast information. High-frequency signals are spaced outside the center of the k-space data, and these high-frequency signals communicate spatial resolution or sharpness

information. The field of image reconstruction is undergoing a paradigm shift right now. Transform-based or optimization-based techniques have typically dominated image reconstruction. Data-driven machine learning approaches, notably Deep learning, have recently been demonstrated to have a considerable advantage over earlier methods for image reconstruction in recent study. Several deep learning frameworks have been described, including AUTOMAP [68], and experimental results have indicated that traditional and compressed sensing-based reconstruction techniques provide higher-quality image reconstructions. The problem of large volumes of training data has been overcome by restricting the number of trainable parameters [69], [70]. However, a number of disadvantages have been identified, including the computational cost of existing techniques [68], the fact that some frameworks do not apply to parallel imaging [71], and the need for theoretical analysis to explain why the algorithms work [69].

3.5 Image Reconstruction Approaches in Low field MRI

In developing countries, low-field MRI equipment can provide an economical, long-term, and safe imaging option to high-field MRI and computed tomography (CT) for brain imaging [8]. Hömmen et al. [10] also discovered that existing extreme low-field MRI systems can generate the needed signal-to-noise ratio (SNR) for clinical imaging. According to Huang et al. [11], portable low-cost MRI equipment can provide a point of care and fast MRI diagnosis, especially in low-income countries where 0.1 MRI scans per 1,000,000 persons are common [12] [13]. Several studies [8], [14] have found that low-field MRI scanners have a low signal-to-noise ratio (SNR), resulting in noisy images. Hömmen et al. [10], who discovered that image artifacts have an impact on reconstruction quality, backed up this claim. It is vital to conduct a systematic evaluation of the image reconstruction approaches utilized in low-field MRI in light of recent breakthroughs and numerous influential publications in the field. This section aims to familiarize readers with relevant knowledge, literature, and the most recent updates on state-of-the-art image reconstruction techniques that have been employed in low field MRI, as indicated in Table 2 below, with their objectives, outcomes, and areas for improvement.

Table 2: Overview of image reconstruction techniques in low-field MRI, and areas for improvement

Reference	Objective	Results	Area(s) of improvement
[14]	Established a universal MRI signal model that describes the link between measured signal and image that is more suited to low-field MRI	Experimental results revealed that the proposed algorithm produced better results and therefore preferred.	Though less evident, the suggested technique produces aliasing artifacts in the lower half of the image.
[44]	This study focuses on super-resolution, which is the process of reconstructing a high-resolution image from one or more low-resolution images.	Due to the greater signal-to-noise ratio per pixel, simulations demonstrate that super-resolution reconstruction can produce better results than direct high-resolution reconstruction in an extremely noisy scenario.	Blurring was not taken into consideration.
[45]	To develop a method for reconstructing images using direct linear inversion (DLI).	The results show that the approaches' reconstruction errors are influenced by the strength of the contemporaneous gradients.	To completely remove the distortions, more study is required.
[46]	An adaptive-size dictionary learning algorithm is a proposed algorithm that combines information-theoretic criteria and Dictionary learning techniques.	When compared to existing state-of-the-art methods, the suggested approach consistently outperforms them in terms of PSNR, SNR, and HFEN.	integrating the proposed algorithm with an image denoising function may help to eliminate noise from noisy images produced by Low-Field MRI equipment.
[47]	Proposed an algorithm for image reconstruction and denoising using a two-level Bregman iterative technique with OMP for sparse coding and SimCO for Dictionary Update and Learning.	The results show that our suggested approach produces improved, practically noise-free image reconstructions.	The proposed algorithm over smoothens the image edges.
[48]	Present an algorithm for image reconstruction in low-field MRI using ASDLMRI for image reconstruction and a nonlinear diffusion filter for image denoising.	The suggested approach is effective in denoising images during reconstruction, according to experiments on visual quality.	A segmentation function needs to be added to the proposed algorithm in the future study.
[50]	implement, test, and evaluate popular denoising algorithms	All of the algorithms removed more than half of the noise in the images, according to the results.	Trilateral filters must be implemented, with the smoothing process

	(Median, Gaussian, Wiener, Anisotropic-diffusion, and Bilateral filters) for low-field MR image denoising	However, at some point, the smoothing process tends to combine the unrelated regions.	taking into account geometric, photometric, and local structural orientation similarities between surrounding pixels in inhomogeneous regions.
[72]	Proposed a multiplicative regularization approach for image reconstruction in low field MRI.	Experimental results revealed that the proposed approach can be used for both image reconstruction and denoising tasks.	Need for edge preservation especially with low SNR signals
[73]	To reconstruct images based on the back projection imaging method utilizing the maximum likelihood expectation maximization (MLEM) algorithm	The imaging resolution reached $1.8 \times 1.8 mm^2$.	More work is needed to improve imaging resolution in a reasonable amount of time.
[74]	Proposed an end-to-end deep neural network methodology (AUTOMAP) for improving the image quality of noise-corrupted low-field MRI data.	AUTOMAP enhances image reconstruction of data obtained on two low-field MRI systems: human brain data and plant root data, displaying SNR increases over Fourier reconstruction.	The fully connected layer requires a lot of memory, which is a key disadvantage of AUTOMAP [26].
[75]	To investigate how much to improve the reconstruction of images from a low-cost MRI-scanner prototype	The quality of the results is insufficient for diagnosing, say, hydrocephalus. However, The reconstructions improved dramatically as a result of the simulated expansion.	More experiments are needed using measured data to determine the feasibility of the algorithm.
[76]	To correct for image distortions produced by standard Fourier reconstruction techniques on low field permanent magnet MRI systems	Iterative conjugate phase reconstruction (CPR) produces images that are comparable in quality to iterative model-based (MB) reconstructions. Iterative MB reconstruction, on the other hand, outperforms iterative CPR in terms of signal intensity correction for stronger inhomogeneities.	In each iteration of the proposed approach, the two most expensive tasks are updating the Split Bregman (SB) system matrix and reconstructing the two images. Parallelization can greatly speed up these processes.
[77]	To solve the major constraints in image reconstruction for low-field MRI using a deep learning (DL) approach.	With synthetic data, DL produces high-quality images.	Neural networks can find a signal-to-image mapping, implying that this concept can be applied to real-world data, and therefore

requires further investigation.

4. Conclusions And Recommendations

In developing countries, low-field MRI devices can provide an economical, long-term, and safe imaging alternative to high-field MRI for hydrocephalus brain imaging. The signal-to-noise ratio in these scanners is much poorer due to the lower magnetic field strength. Inhomogeneities are also present, meaning that the inverse Fourier Transform method of collecting the image is no longer possible. There is little study in the literature on applying image reconstruction techniques to improve the quality of images from low-field MRI scanners. These techniques include iterative methods like [14], dictionary learning methods like the approaches proposed in [46], [47], [48], and deep learning methods like AUTOMAP [74]. Experimental results from the literature revealed improved image quality of the reconstructed images. However, some studies used synthetic data in their experiments [75], [77], and therefore more experiments are using measured/real-world data. Studies using deep learning approaches in low field MRI were very limited, during this study, we managed to identify and retrieve only two articles [74], [77]. However, deep learning approaches have been used for image reconstruction in high field MRI [78]. This implies that further research needs to be done on the possible applications of deep learning approaches for image reconstruction in low field MRI since deep learning has succeeded in other tasks like image classification [79]. Also, integrating deep learning and dictionary learning approaches may be of interest to future researchers.

Abbreviations

MRI: magnetic resonance imaging; SNR: signal-to-noise-ratio; CNR: contrast-to-noise ratio; ML: machine meaning; DL: dictionary learning; GPUs: graphical processing units.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

Not Applicable.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

Emmanuel Ahishakiye (EA) and Johnes Obungoloch (JO) designed the study. EA wrote the manuscript. JO edited and extensively reviewed the manuscript. All the authors approved the manuscript.

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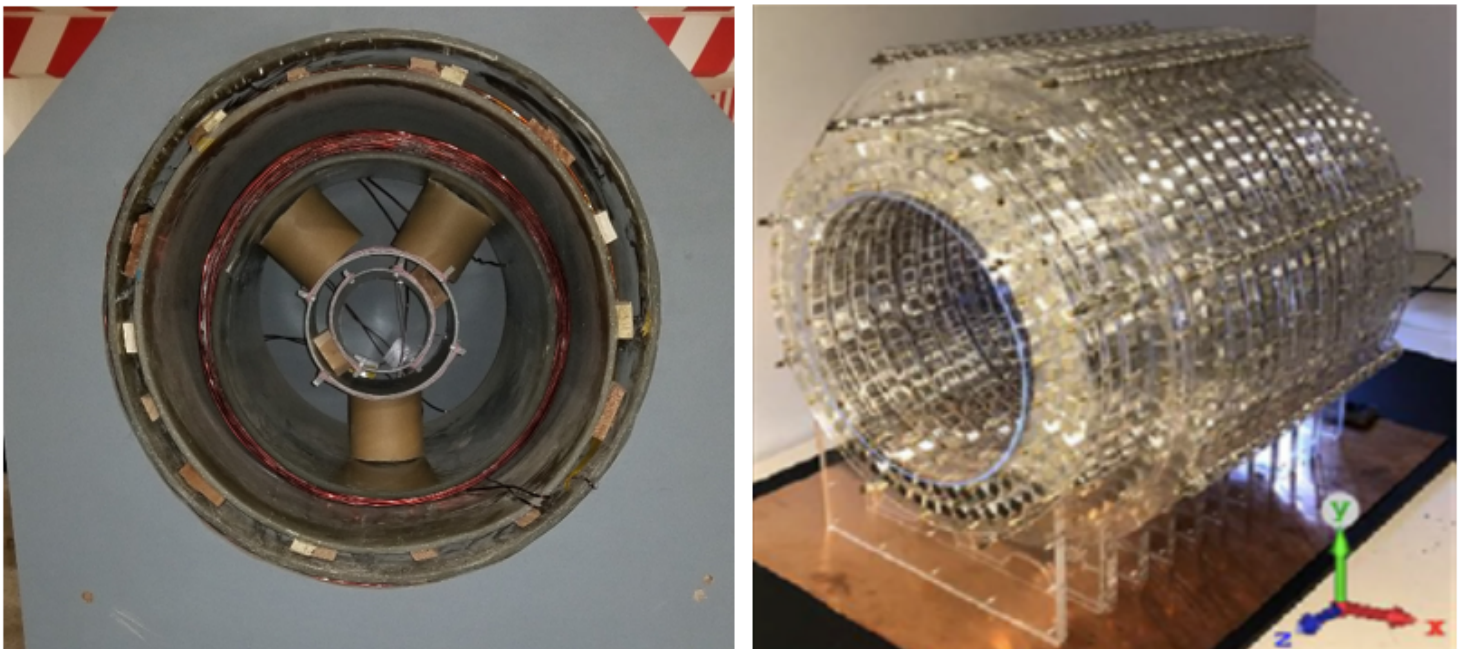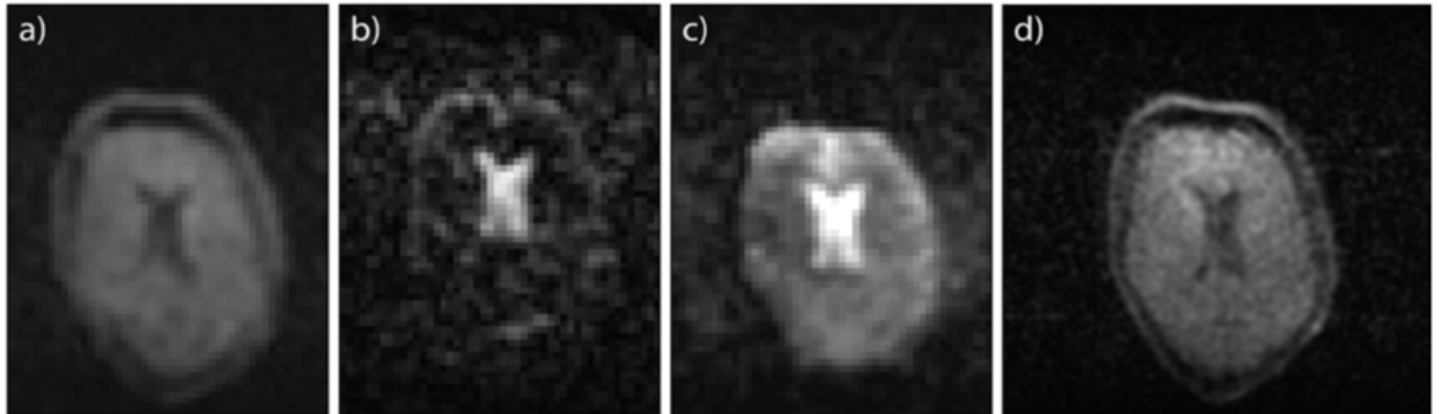
Figures

Figure 1

The low-field MRI prototypes. The left is the PSU-MUST prototype, adapted from [8]; and the right is the LUMC prototype, adapted from [32].

Figure 2

Images showing relatively high SNR but also image distortions obtained from the low field MRI scanners under development. Images were acquired with different weighting at a spatial resolution of 4 × 4 × 4 mm: T1-weighted (2.5-minute data-acquisition time) (A); T2-weighted (2 minutes) (B); inversion-recovery turbo spin-echo sequence (2 minutes) (C); and higher resolution image (2 × 2 × 4 mm) from a different volunteer (13 minutes) (D). Adapted from [51].