Artificial Intelligence Techniques for Motion Artefact Correction in Magnetic Resonance Imaging

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(Dated: May 15, 2024)

Abstract

Contemporary advancement of Artificial Intelligence (AI) has significantly permeated the medical imaging field. In the case of Magnetic Resonance Imaging (MRI), motion artefacts requiring correction present considerable potential to benefit from these technologies. Despite the increased uptake in research on this subject, there is still a notable deficiency in data to encourage clinical implementation of this technology more widely. By carrying out a comprehensive literature search across relevant databases, this review explores emerging AI technologies for correcting motion artefacts in MRI. The results indicate that AI tools are effective in MRI motion correction, primarily when combined with traditional techniques. However, challenges persist including the scarcity of training data and the time-intensive model training. Consequently, this review presents an evaluative discussion that acknowledges the obstacles and prospects that accompany the evolving landscape of motion correction in MRI. I end with a recommendation for future research to employ a hybrid approach to motion correction techniques and the production of diverse training data sets.

I. BACKGROUND

A. MRI Principles

Magnetic Resonance Imaging (MRI) is a medical imaging technique used to examine soft tissues in the body. It utilises the hydrogen ion – a proton – which is found in both water molecules and fat making up the majority of the human body. This is significant because most diseases can detected by an increase in water content [1]. The static magnetic field employed by the MRI machine, causes the protons in the body to align with the magnetic field. Radio wave frequency (RF) coils in the MRI machine produce a short RF pulse, causing only protons with the same resonant frequency to align with the RF pulse. This resonant frequency is known as the Larmor frequency, ω, and is determined by the Larmor equation,

$$\omega = \gamma B, \tag{1}$$

where γ is the gyromagnetic ratio and B is the magnitude of the applied magnetic field. The RF coils receive the emitted signals and can locate where in the body they originated from by the frequency of the signals received. The intensities are then plotted on a grey scale to create the final Magnetic Resonance (MR) image [1]. For a broader understanding of MRI, see Ref. [2].

Medical imaging is essential to medical diagnoses and treatment processes with imaging data accounting for about 90% of all healthcare data [3]. When compared with other common imaging modalities such as Computed Tomography (CT), Positron Emission Tomography (PET) and X-ray imaging, MRI is safer as it does not use ionising radiation – hence avoiding the risk of inducing malignant disease and genetic mutations [2]. Along with being non-invasive, MRI has no known biological hazards [1]. This places MRI at the centre of the medical imaging discipline, being used as a diagnostic tool for conditions like cancer, stroke and multiple sclerosis (MS) [4, 5, 6]. However, MRI is not without its shortcomings – it is prone to artefacts due to the complex interactions between the components in the MRI machine and the reconstruction algorithm used [7].

B. Motion Artefacts in MRI

Artefacts manifest as image features that are not present in the original object – for MRI, motion artefacts are by far the most common of all [8]. They are the result of patient motion, of which there are two types: irregular bulk motion (e.g. peristalsis, involuntary movements) and regular, pulsatile motion (e.g. blood and CSF flow). Patient motion can appear as blurring or ghosting or both in the MR image (see Fig. 1). This is explained by incorrect allocation values of the k-space signal from MRI machines [9]. The prevalence of motion artefacts in MRI is due to scanning times being long compared to the timescale of most physiological motion [10]. Additionally, high resolution MR images necessitate longer scans, increasing the likelihood of motion artefacts in the final image [11]. Long acquisition times are inherent to the function of MRI and, therefore motion artefacts will likely always be present in MRI.

There are many adverse effects that motion artefacts have on patient treatment and outcomes – including increases in the radiation dose supplied to non-malignant tissues [12], the production of non-diagnostic images [13], delayed treatment [14] and inaccurate tumour segmentation [15]. Tumour segmentation is a time-consuming pro-

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cess for an oncologist, potentially taking more than four hours per case [14]. If motion artefacts are corrected, these time constraints can be eased, and oncologists can segment tumours more quickly and accurately. Moreover, motion artefact correction could result in patients receiving treatment sooner than they would otherwise. This is significant because just “a four week delay in treatment is associated with an increase in mortality across all common forms of cancer treatment” [16] – thereby highlighting the increasing importance of motion artefact correction.

Motion artefact mitigation strategies can be put into three main categories: motion prevention, artefact reduction and motion correction. Throughout this review, I will use the term ‘motion correction’ to refer to the explicit estimation and compensation of motion as a retrospective technique. Traditional motion mitigation strategies include motion prevention training, feeding babies before the scan and fast imaging [17, 18]. The wide variety of imaging techniques and motion types that occur in MRI means that there is no universal methodological solution to mitigate motion artefacts. Instead, there is a range of methods each suited to specific medical imaging contexts [19]. This motivated the focus of this review.

C. AI in MRI Correction

There is a growing body of literature that recognises the use of Artificial Intelligence (AI) in medical imaging – in particular, Convolutional Neural Networks (CNNs). CNNs are a type of Deep Learning (DL) model used extensively in medical imaging. They are considered the most successful image analysis model [20]. This supports research which proposes that DL methods have the potential to provide a faster and more scalable alternative to more conventional neuroimaging analysis pipelines [19]. These notions highlight the growing recognition and application of AI in medical imaging. In the particular context of MRI motion correction, if AI can be trained to compensate for motion, enhance efficiency and refine data analysis, then it may be a viable technique to advance motion correction tools.

What follows is a review of AI, Machine Learning (ML) and DL methods and their efficacy in MRI motion artefact correction. The technical details of the algorithms are intentionally omitted, as they are no longer considered new and are well-covered in numerous other works [3]. Rather, this review will focus on evaluating the emerging techniques and how they meet the needs of motion artefact correction.

II. METHOD

This review sought to assess the use of AI techniques for correcting motion artefacts in MR images. Below I outline the key features of my methodology.

I decided to narrow my scope to a single medical imaging modality and a specific artefact type. This allowed for a more in-depth focus criteria. I used the PICO concept (Patients, Intervention, Comparator, Outcomes) to formulate answerable questions. Key terms like ”MRI”, ”motion artefact”, “motion correction” and ”deep learning” were picked out of the questions and combined with Boolean operators to refine the search [21]. Initially, the Google Scholar database was used, however, it cannot be relied on for current medical information or practice [22]. Therefore, the search strategy was amended to use the PubMed and Science Direct databases to find relevant studies. Using different databases allowed me to engage with diverse perspectives, providing a more comprehensive range of studies and articles to evaluate.

I did not exclude any studies specifically but rather chose as relevant to the topic. To ensure the reliability and validity of the findings of this review, I considered only peer-reviewed articles and studies. Grey literature was not included as it is often difficult and time-consuming to identify relevant studies [23]. Moreover, it may not meet the quality of peer-reviewed literature.

The search was not restricted by publication date or geography, but it was limited to English. Despite this, I aimed to use recent papers and studies to reflect this rapidly evolving field.

III. RESULTS

In this section, I first consider traditional approaches to motion correction and then DL approaches that have emerged more recently. Through a critical analysis of the diverse approaches that have been applied in this field, I show the tensions and possibilities to create a holistic picture of the current state of the field.

A. Traditional Approaches

Imaging interpretations can be carried out by diagnostic technicians and clinicians but there are many technologies used to correct motion in MR images. Motion correction usually involves the explicit estimation and compensation of motion [10]. Traditional methods of making these corrections can range from computer-aided detection to image segmentation and reconstruction. ‘PROPELLER’ which stands for ‘periodically rotated overlapping parallel lines with enhanced reconstruction’ was evaluated for its effectiveness in motion correction and image quality of the upper abdomen [24]. Using a control sample of 20 healthy adult volunteers they found overall image quality was significantly improved.

Another study compared echo-planar imaging (EPI) with PROPELLER for prostate MRIs in patients with previous total hip replacements and it was found that PROPELLER demonstrated better image quality and

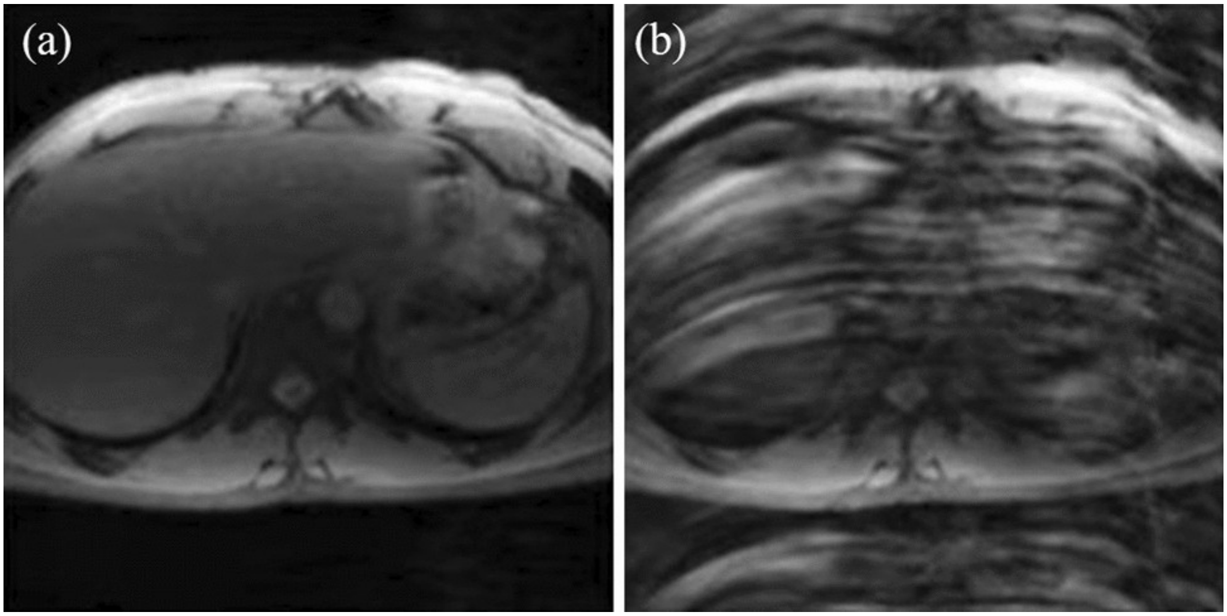

FIG. 1. Effect of breathing motion on the MRI. (a) MRI taken when the breath is held. (b) MRI taken when the patient is freely breathing. The MRI scan in (b) depicts multiple copies of the outer edges being created and different frequency encodings resulting in ghosted blurry images due to free breathing [17].

significant artefact reduction compared to EPI [25]. These studies highlight the effectiveness of traditional reconstruction methods but they also show how motion correction can vary across methods. Some literature states that even traditional correction methods are still limited as they can be computationally intensive and include sophisticated algorithms [19, 10]. Similarly, when comparing images using the long-term averaging method (LOTA), it was found that most methods require either an increased acquisition time, result in additional patient-related motion artefacts, or additional hardware or postprocessing software [26].

Returning to the idea that image interpretations are carried out traditionally by humans, further emphasises these limitations and segways into discussions about how AI tools such as DL can automate image analysis and provide support to physicians [3]. Such assistance is extremely beneficial for improving accuracy in MRI motion correction.

B. AI-based Techniques

AI is an increasingly fascinating subject for researchers within the field of medical imaging. Many recent studies have shown particular interest in DL algorithms such as CNNs for correcting motion artefacts in MR imaging [27, 28, 29]. In 2018, the use of CNNs was proposed for the quantification and localisation of motion artefacts [28]. Additionally, they proposed a visualisation technique to highlight the dominant features in an input image for a given trained network. This technique has several attractive features. For one, it could be especially useful for identifying potential areas of bias in the CNNs. It could also serve as a way of better understanding the classifications or elements that the algorithm takes into account when making decisions. Rigid head motion and non-rigid respiratory motion were the main focus of this study and this resulted in clear differences being observed between data sets with and without motion. By focusing on different types of motion and different body parts, their approach demonstrates the versatility of CNNs in handling varied data sets. Furthermore, the automated detection of motion artefacts showed prospective and retrospective image quality assurance which contributes to improved image analysis in MR imaging.

Automatic quality control features using ML methods were researched further in a more recent study [29]. Interestingly, they acknowledge the limits of complex AI models and deep neural networks. To combat this, they investigated two versions of a three-dimensional (3D) CNN and the best model of the two was further compared to the best-performing IQM-based model. This study shows the effectiveness of DL methods in line with the findings of the previous study. It goes further to recognise that neural networks learning to extract and represent task-relevant features is a key difference between DL and traditional methods. It would be interesting to see how these findings can be expanded in future studies, perhaps to compare other imaging modalities as they suggest.

DL in neuroimaging motion artefact correction is another relevant focus area that came up in my search. Haskell et al. introduced a motion correction method, Network Accelerated Motion Estimation and Reduction

(NAMER), for two-dimensional (2D) brain imaging. It is based on an iterative algorithm which combines a trained, artefact-detecting CNN with a non-linear optimisation and a model-based reconstruction. It was shown that this method enabled rapid motion correction of MR images, in both simulated and in vivo contexts. The extent of the correction was determined by the image space root mean square error [30] and can be seen in Fig. 3. This study shows how AI can work with other tools to correct motion artefacts.

These findings are supported by Al-masni et al.'s research, which showed significant improvements in the overall image quality of the motion-corrected images via the proposed motion correction network [27]. Despite acknowledging promising motion correction models such as NAMER in Haskell et al.'s study, and CNN prediction in Wang et al's study, they suggested the need for a model requiring less execution time. This study therefore proposed a new DL architecture by designing efficient stacked U-Nets with self-assisted priors to solve the problem of motion artefacts in MRI. U-Nets being a specialised type of CNN. Furthermore, both simulated and real motion data were tested to recover the motion-free image from the motion-corrupted image. More recently, Kang and Lee applied U-Net models to remove motion artefacts from brain MR images (see Fig. 2) – this exhibited high performance when provided with ideally paired data sets [31]. Al-masni and Kang and Lee both show that DL tools can improve MR image quality.

These results show the efficacy of DL methods, in particular CNNs and U-Nets, for MRI motion correction. In the next section, I will critically interpret these findings and discuss their implications for the field, both now and in the future.

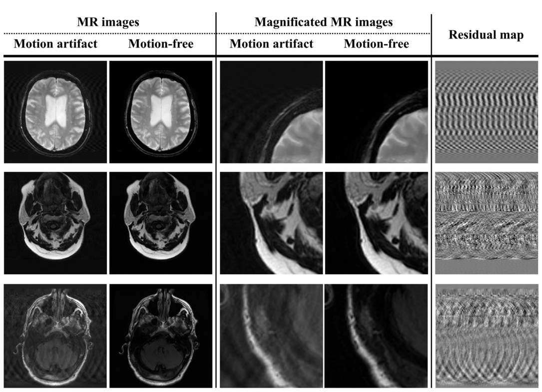

FIG. 2. Simulation-based motion artifacts and motion-free magnetic resonance images with residual maps [31].

IV. DISCUSSION

In the Results section III, the efficacy of AI tools in MRI motion correction was shown. Furthermore, I identified significant factors that influence discussions around this topic. In this section, I delve further into some key considerations such as processing time, data processing and hybrid techniques to discuss how AI can be an effective tool for motion artefact correction in MRI.

A. Processing Time

Processing time is a continually significant consideration for researchers in MRI studies [10, 13, 27]. MRIs are time-consuming by the nature of their complex technology. They take time to capture detailed multiplanar images [2] and require limited movement to reduce motion artefacts. This can either reduce the diagnostic usefulness of the scan or necessitate a repeat scan [32]. In addition to this, the process of annotating medical images is also time-consuming. In a UK context, for instance, this could mean long turnaround times and even longer waiting times under the NHS public healthcare system. In light of these challenges, AI may represent an idealised abstraction for its potential to correct artefacts, automate image analysis and improve imaging processes. While some researchers have criticised the long time needed for training DL models [9], others have recognised that despite an initial long training time, DL models like CNNs can offer benefits such as real-time image reconstruction [13]. This becomes even more challenging if we consider individual clinics and hospitals. A potential mitigation could be to train algorithms on diverse data sets to encourage generalisable DL models – cutting out the need for smaller institutions (e.g. individual hospitals) to train models themselves. Moreover, it could increase time-savings and assist in the adoption of DL motion correction techniques.

B. Data Processing

Data processing is a crucial procedure in ML. It typically involves data acquisition, data preparation, data processing, model training, and result reporting. Across the field, many studies are confronted with the 'data challenge' [3] – this refers to the limited data available for DL training. For DL tools with complex architecture extensive training is required to counteract overfitting [29]. An overfit model has difficulties providing accurate results for data different from the test data set. This is where motion simulation tools such as View2Dmotion can assist [9]. Simulation experiments demonstrate that simulation tools can be used to increase the size of training data sets [33, 31]. Therefore, simulation tools can offset the 'data challenge' for motion correction.

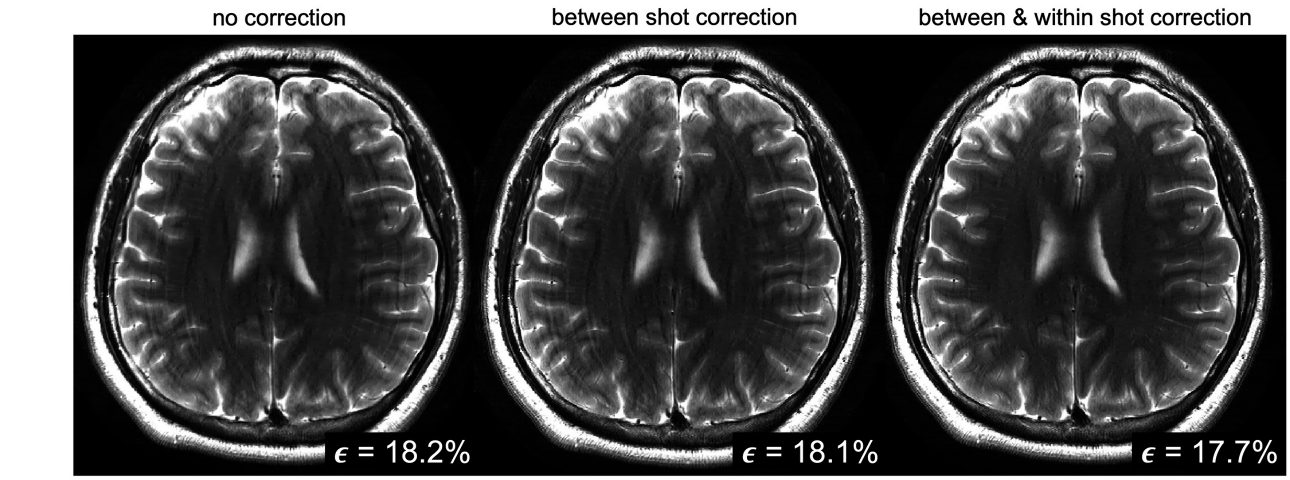

FIG. 3. NAMER in vivo inter- and intrashot motion correction. Reconstructed images assuming no motion occurred, correcting for motion between shots (intershot correction), and correction results after allowing fine-tuning of the motion parameters for each line of k-space at highly corrupted shots (intrashot correction). Motion artifacts are significantly reduced by allowing the motion parameters to vary across the lines within a shot, as shown in the right column. Data consistency error values are shown in the bottom right of each image [30].

C. Hybrid Techniques

Adopting a hybrid technique that utilises AI tools alongside traditional approaches for MRI motion artefact correction could be a promising advancement. Multiple studies have shown AI as a beneficial tool with the potential to correct motion artefacts in MRI [30, 27, 33]. Some have suggested that it is similarly effective to other clinical methods [31, 29]. While others have explicitly argued for a multifaceted "toolbox" approach as no single method can be applied effectively in all imaging situations [10]. These different research perspectives highlight the nuances that exist within the field. Consequently, adopting a hybrid approach acknowledges the complexity of motion artefacts and has been shown to increase the efficacy of motion correction methods in MRI. This approach also shows promise for other imaging modalities and artefacts [34, 35, 36].

In this section, I interpreted the results of this review. While acknowledging the recent technological advancements, I also recognise some limitations, such as long processing times and a lack of available training data. Nevertheless, DL models such as CNNs and U-Nets are shown to be significant tools for MRI motion correction. Their ability to process large amounts of data makes them particularly useful in this context, especially when implemented as hybrid techniques.

V. CONCLUSIONS

This review has depicted an overview of the current advancements of DL in the motion correction of MR images. The main message of this survey is to present the benefits that AI techniques bring to motion artefact correction and their resulting improvements to patient treatment and outcomes. This review serves as a resource to guide researchers and professionals in their understanding of the current state of motion artefact correction in MRI. What is now needed is the sharing and aggregation of data across institutions to support the development of robust, generalisable AI models (Huynh et al.). Future research can and should build on this to analyse and examine how AI can optimise motion artefact correction for other medical imaging modalities and continue to advance medical imaging more broadly.

ACKNOWLEDGMENTS

I wish to thank A. Robinson (Cambridge University Hospitals NHS Foundation Trust) for supervising this review.

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