An approach to coil calibration based on prior training data

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Introduction: Measurement of receive array coil sensitivities has become an intrinsic part of almost all MR exams. The calibration is used to enable parallel imaging (PI) or correct signal modulations due to local receiver array coils. Currently such calibration is relatively rapid (typically 30-60s) and so is not unduly intrusive into the exam. However the time needed to calibrate coils is related to the size of the coils which make up the array. As coils become smaller, higher resolution images are needed for calibration and so calibration times will increase. Calibration is also prone to error when the subject moves between calibration and acquisition (pre-scan calibration) or during acquisition (integrated or 'auto' calibration). The potential of parallel transmit (PTx) further increases the complexity and time taken to calibrate array coils as both the transmit (B1) and the receive fields require calibration leading to calibration times of many minutes[1]. Calibration is necessarily performed on a subject by subject basis due to the interaction between subject and array coil which changes the individual coils sensitivity, however no knowledge of prior calibrations is currently used to inform the calibration process, on a typical system 5 or more calibration scans may be acquired per day which could be used as a large library of possible calibrations. The aim of this work was to explore the variation in receive coil sensitivities across a number of subjects and using this as a training dataset construct a compact model of coil sensitivity variation which could be used to reconstruct unknown individual coil sensitivities reducing or removing altogether the need for individual coil calibration.

Theory: Principal component analysis (PCA) is widely used to reduce multidimensional datasets to lower dimensions. Using PCA compact parameterized predictive models of new data can be constructed [2]. In this work a data matrix is constructed by reforming each whole volume of coil sensitivity data into a single vector for each coil, multiple measurements taken from different subjects are then compiled as columns into a data matrix (the training data).The ordered eigenvectors of the covariance of this matrix give us the principle modes of variation (principal components, PC) of the data. N PC's are generated where N=the number of measurements (the number of training datasets). A weighted linear combination of these N components can exactly replicate any of the coil sensitivities in the training dataset. The only parameters to be determined are a single scalar weight for each component. If the span of all typical variations in the input data are captured by the training data then a weighted linear combination of these components can replicate data that is not part of the training data. A favorable case is when a few of the PC are dominant as this allows effective description of new coil sensitivities in terms of only the coefficients of these PC.

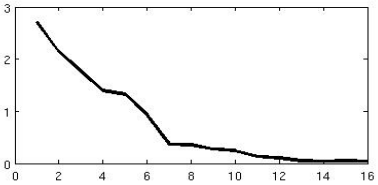

Figure 1. Mean %RMS error per pixel plotted as a function of number of principle components used to model a single coil.

Methods: A Philips 3T system was used with an 8 channel rigid head array coil. 12 volunteers were scanned (some twice, with repositioning) to generate 17 whole head complex 3D datasets. The acquisition was a low resolution field echo (TR/TE 10/3ms, 3 averages, resolution 128x64x64, zero filled to 128x128x128.) The acquisition geometry was fixed in magnet co-ordinates with its centre at isocentre of the magnet. Total acquisition time for this volume was 122s. The position of the head array coil relative to isocentre was subject to positioning error of the bed but no explicit account was made for this. Coil sensitivity maps were generated from this data by dividing images from each coil element by the sum of squares of all the coils. After removing one dataset (to be used as the target data to test the method) A data matrix was constructed for a candidate single coil from the array (matrix size 16x ~2million) and the principal components determined. Test 1: The sensitivity of each individual coil of the omitted array data was fitted using a variable number of PC and difference between the native and fitted sensitivities determined as a function of the number of coefficients used. Test 2: A simulated image dataset undersampled by a factor 2 was made from the Shepp-logan phantom using the measured sensitivity of the omitted array coil data. This data was then reconstructed using the PC weights as free parameters for a single coil from the array (the others were correct) The PC weights (between 1 and 8 free parameters) were determined by minimizing inconsistency between multiple SENSE reconstructions based on different subgroups of the coils. This approach requires an over-determined system, more coils than the acceleration factor, but does not require a known gold standard[3,4] and so is consistent with a truly unknown sensitivity .

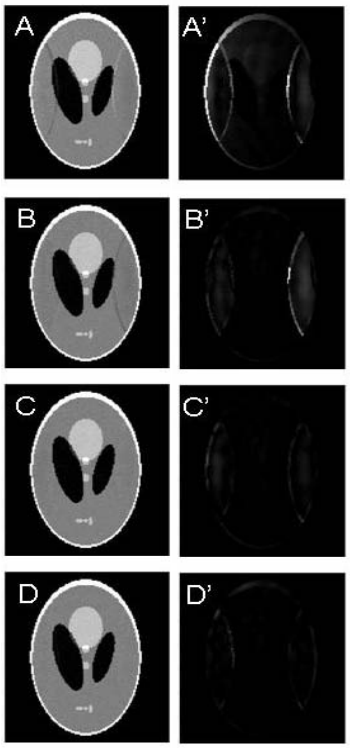

Figure 2. Parallel imaging reconstructions, acceleration factor = 2 number of coils = 4. One of the coils was treated as an unknown. A uses 1 PC, B, 2 PC, C, 5 PC and D 8PC. A'B'C'and D' show the difference from a gold standard reconstruction where all coils were known. Full scale (white) in the difference images = 15% RMS deviation

Results: Figure 1 shows the mean percent root-mean-square (%RMS) error between the fitted coil sensitivity and the measured sensitivity averaged over the whole image for a single example coil in test 1 as a function of the number of PC used. It can be seen that 99.5% accuracy is achieved with only 8 components. Averaging over all coils and repeated tests where each one of the 17 datsets were in turn excluded leads to exceeding 99.5% accuracy for 8 PCs Figure 2 shows parallel imaging reconstructions (left) and error (right) for an example of test 2 in which the unknown PC weights for 1(A) 2(B),5(C) and 8(D) components directly by optimizing the consistency of reconstructions from subsets of 4 coil elements. 5 PC are enough to virtually eliminate the residual error. The mean %RMS error in D was 0.7%

Conclusions: Coil sensitivity data is generally measured over a whole volume using around 32000 complex Fourier terms per coil. This exploratory work indicates that with appropriate training data from other subjects this can be compressed to between 5 and 10 scalar terms per coil element while still achieving coil maps with a high degree of accuracy that is sufficient for effective PI reconstruction. The data used for this study was acquired using standard low resolution acquisitions, optimised for speed and is subject to errors due to imperfect cancellation of anatomy in regions where coil spatial variation is rapid. This small but significant perturbation appears to increase the number of PC required. Acquisition of high resolution training data may be expected to increase the compressibility further as it will exclude these errors. Further compression may be achieved by treating all coils elements together in a single data matrix as variation is clearly coupled between coils. This apparatus in its current form is limited to fixed coils but if knowledge of the coil positions can be obtained (using MR visible markers for example) then freely positionable coils could also be included in this framework. Although 17 training datasets used were sufficient for this proof of principle it is likely more would be required in practice. It would be relatively straightforward to acquire a large number training sets as each is simply a volume dataset. It is envisaged that when a new coil is developed by a manufacturer a training set of several hundred scans could be rapidly acquired from several sites and this could form the training set to allow subsequent rapid coil calibration.

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