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Computer-generated fMRI phantoms with motion-distortion interaction

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Abstract

As an extension of previous work on computer-generated phantoms, more accurate, realistic phantoms are generated by integrating image distortion and signal loss caused by susceptibility variations. With the addition of real motions and activations determined from actual functional MRI studies, these phantoms can be used by the fMRI community to assess with higher fidelity post-processing algorithms such as motion correction, distortion correction, and signal-loss compensation. These phantoms were validated by comparison to real echo-planar images. Specifically, studies have shown the effects of motion-distortion interactions on fMRI. We performed motion correction and activation analysis on these phantoms based on a block paradigm design using SPM2, and the results demonstrate that interactions between motion and distortion affect both motion correction and activation detection and thus represent a critical component of phantom generation.

Keywords

susceptibility; field inhomogeneity; phantom; simulation; functional magnetic resonance imaging

Introduction

The observation of blood oxygenation level-dependent (BOLD) signals [1] is well recognized in functional magnetic resonance imaging (fMRI) studies. Unfortunately, the acquired fMRI data is often degraded by gross motion, physiological activities such as respiration and cardiac motion, and susceptibility artifacts. Computer-generated phantoms

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have recently been developed for the evaluation of fMRI pre-processing algorithms [2;3]. The phantoms were created from data obtained from real echo-planar images (EPI), and the motion sequences were modeled on real fMRI data. The effects of static-field inhomogeneity, which are also called “susceptibility artifacts”, were not considered properly in this model. By remedying this weakness, we can strengthen the fidelity of these phantoms as an evaluation tool for fMRI studies.

With an MR simulator, simulated phantoms with controlled characteristics and known ground truth can be produced. Many MR simulators have been developed [4-11] so far. Petersson *et al.* proposed a fast simulation approach based on k -space formalism [11]. However, most of the artifacts in MR images such as static-field inhomogeneity, or chemical shift can not be modeled in this way. More sophisticated MR simulators [4-8] are based on solving the Bloch equations. Complex spin modeling was adopted to simulate different kinds of artifacts and pulse sequences although the computation time is increased so dramatically that it becomes impractical for many applications such as fMRI. Parallel computing techniques have been employed to speed up the complex computation [9].

While most existing simulators aim to produce a static MR image, recently several groups have simulated dynamics scans like fMRI where motion artifacts and motion-distortion interactions play a role [12-14]. A functional MRI simulator that solves the Bloch equations with rigid-body motion artifacts was developed by Drobnjak et al. [10]. Most of the characteristics that have been seen in fMRI data were integrated in the Bloch equations including in-scan motion, static-field inhomogeneity, chemical shift, spin history, and Eddy current. These integrated functions will benefit the theoretical study of these artifacts in fMRI, but the increased computation complexity is substantial. This paper presents a method for the creation of fMRI phantoms using an MR simulator tailored specifically to gradient-echo, echo-planar images. Rather than modeling complex spin behavior for multiple events as we have described in [8], we derive an imaging equation in the presence of B_0 field inhomogeneity and compute the MR signal directly from it. We ignore some image features which are minimized in modern MR scanners, such as imperfect slice selection profile, eddy currents, and image distortion in the readout direction, to obtain affordable computation efficiency for the modeling of more serious problems arising from intravoxel dephasing and distortion in the phase encoding direction.

2. Material and Methods

In this section, we present the development of realistic fMRI phantoms using computer simulation. We use an existing MR simulator [8] to compute the static-field inhomogeneity induced by the susceptibility difference in the human head. Results show that the field inhomogeneity patterns we produce are similar to those in the field map measured in real MR scanner. We include the effects of spatially varying spin density, $T1$, and $T2^*$. We simulate $T2^*$ -weighted EPI images by computing the MR signals via the Bloch equation. Image distortion and signal loss in echo-planar imaging are produced by the incorporation of a field inhomogeneity map. We also describe how to apply motion to these phantoms and to model functional activations.

2.1 Calculation of static-field inhomogeneity

Static-field inhomogeneity in the human head is caused primarily by the susceptibility difference between air and tissues, and a map of the inhomogeneity can be numerically calculated [8;15-18], if the spatial distribution of susceptibility is given. The approximate susceptibility distribution is obtained by identifying the air cavities in the human head. This is done by segmenting an anatomical volume into air and tissues. Because the susceptibility of all brain tissues are close to that of water, we can approximate the susceptibility distribution by multiplying the voxel-based binary volume by the susceptibility of water -9.05×10^{-6} (the susceptibility χ_m of a substance, which is the ratio between its magnetization $M = \chi_m H$ and the applied field H induced by the magnet, is unitless). This map of susceptibility $\chi_m(\mathbf{r})$ is then taken as input to an MRI simulator [8], and the induced field inhomogeneity is numerically calculated.

2.2 Determination of spin density, T1, and T2*

An automated model-based tissue segmentation technique [19] is employed to segment an anatomical volume into white matter, gray matter, and CSF. From this segmentation, three voxel-based brain “tissue volumes” representing white matter, gray matter, and CSF are created. Each tissue volume is also associated with its approximate spin density, $T1$ value from the literature [8;20;21] and $T2^*$ value measured experimentally.

2.3 Generation of EPI signal

The tissue volumes associated with their properties define the object, or phantom, from which we simulate an EPI image. In the presence of static-field inhomogeneity, we compute the k -space data for EPI sequence with specified imaging parameters. At each point in time, the signal can be represented as an integral over the object space. Since our phantom is a discrete representation, the continuous human head and continuous static-field inhomogeneity must be approximated. Figure 1 depicts our method.

Each discrete object voxel is assumed to have constant spin density, $T1$, and $T2^*$. To model the intravoxel dephasing effect, we assume that the field inhomogeneity varies linearly across a voxel. With this model, analytical integrals can be carried out in the calculation of the MR signal produced. For a single shot, multi-slice EPI MR sequence, the signal of slice z_1 in the presence of field inhomogeneity B has the following form:

$$\begin{aligned}
 s(k_x, k_y, z_1) &= \int p(\gamma G_z(z + \Delta B(\mathbf{r})/G_z - z_1)) \\
 &\times \rho(\mathbf{r}) \exp\left(-\left(k_y/\bar{G}_y \pm k_x/G_x + TE\right)/T2^*(\mathbf{r})\right) \\
 &\times (1 - \exp(-TR/T_1(\mathbf{r}))) \\
 &\times \exp(-i\gamma \Delta B(\mathbf{r}) TE) \\
 &\times \exp(-i(k_x(x \pm \gamma \Delta B(\mathbf{r})/G_x) \\
 &+ k_y(y + \gamma \Delta B(\mathbf{r})/\bar{G}_y))) d\mathbf{r},
 \end{aligned} \tag{1}$$

where p is the slice selection profile function, γ is the gyromagnetic ratio, k_x, k_y are the k -space components, $\rho(\mathbf{r})$ is the spin density at position $\mathbf{r}$, G_x, G_z are the applied field gradients in x and z direction respectively, $\bar{G}_y$ is the effective gradient in y direction, TE and TR are the echo time and repetition time. Assuming that $|B/G_x| \ll v_x$ and $|B/G_z| \ll v_z$, where v_x, v_y, v_z are the dimensions of a voxel, we have

$$\begin{aligned} s(k_x, k_y, z_1) &= \int p(\gamma G_z (z - z_1)) \\ &\times \rho(\mathbf{r}) \exp\left(-\left(k_y/\bar{G}_y \pm k_x/G_x + TE\right)/T2^*(\mathbf{r})\right) \\ &\times (1 - \exp(-TR/T_1(\mathbf{r}))) \\ &\times \exp(-i\gamma \Delta B(\mathbf{r}) TE) \\ &\times \exp(-ik_x x) \exp(-ik_y (y + \Delta B(\mathbf{r})/G_y)) d\mathbf{r}. \end{aligned} \quad (2)$$

Approximating the integral by a sum of integrals over voxels (x_m, y_n) , assuming that ρ is constant over a voxel and B is linear in x, y, z over a voxel, and assuming that p is a constant over one voxel gives

$$\begin{aligned} s(k_x, k_y, z_1) &= \sum_{mn} \rho^{(m,n)} \exp(-i\gamma \Delta B^{(m,n)} TE) \\ &\times \exp\left(-\left(k_y/\bar{G}_y \pm k_x/G_x + TE\right)/T2^{*(m,n)}\right) \\ &\times (1 - \exp(-TR/T_1^{(m,n)})) \\ &\times \int_{x_m - \frac{v_x}{2}}^{x_m + \frac{v_x}{2}} \exp\left(-i\left(\gamma \Delta B_x^{(m,n)} TE + k_x + k_y \Delta B_x^{(m,n)}/G_y\right)(x - x_m)\right) dx \\ &\times \int_{y_n - \frac{v_y}{2}}^{y_n + \frac{v_y}{2}} \exp\left(-i\left(\gamma \Delta B_y^{(m,n)} TE + k_y (1 + \Delta B_y^{(m,n)}/G_y)\right)(y - y_n)\right) dy \\ &\times \int_{z_1 - \frac{v_z}{2}}^{z_1 + \frac{v_z}{2}} \exp\left(-i\left(\gamma \Delta B_z^{(m,n)} TE + k_y \Delta B_z^{(m,n)}/G_y\right)(z - z_1)\right) dz \\ &\times \exp(-ik_x x_m) \exp(-ik_y (y_n + \Delta B^{(m,n)}/G_y)), \end{aligned} \quad (3)$$

where $\rho^{(m,n)} = \rho(x_m, y_n, z_1)$, $B^{(m,n)} = B(x_m, y_n, z_1)$, $\Delta B_\alpha^{(m,n)} \equiv \partial \Delta B^{(m,n)} / \partial \alpha$, $T1^{(m,n)} \equiv T1(m, n)$, and $T2^{*(m,n)} \equiv T2^*(m, n)$. Carrying out the three integrations yields the following:

$$\begin{aligned}
s(k_x, k_y, z_1) &= \sum_{mn} \rho^{(m,n)} \exp(-i\gamma \Delta B^{(m,n)} TE) \\
&\times \exp\left(-\left(k_y/G_y \pm k_x/G_x + TE\right)/T2^{*(m,n)}\right) \\
&\times \left(1 - \exp\left(-TR/T_1^{(m,n)}\right)\right) \\
&\times \text{sinc}\left(\left(\gamma \Delta B_x^{(m,n)} TE + k_x + k_y \Delta B_x^{(m,n)}/G_y\right) \nu_x/2\right) \\
&\times \text{sinc}\left(\left(\gamma \Delta B_y^{(m,n)} TE + k_y \left(1 + \Delta B_y^{(m,n)}/G_y\right)\right) \nu_y/2\right) \\
&\times \text{sinc}\left(\left(\gamma \Delta B_z^{(m,n)} TE + k_y \Delta B_z^{(m,n)}/G_y\right) \nu_z/2\right) \\
&\times \exp(-ik_x x_m) \exp\left(-ik_y \left(y_n + \Delta B^{(m,n)}/G_y\right)\right),
\end{aligned} \tag{4}$$

The factors on the second line of Eq. (4) represent T2* and T1 weighting, respectively, and the three sinc functions indicate the intravoxel dephasing effects inside an object voxel induced by the field inhomogeneity gradients in the x , y , and z directions, respectively. After we compute the set of signals for all values of the pair $k_x k_y$ within the slice centered at z_1 , a Fourier transform yields the reconstructed image for that slice.

2.4 Creation of fMRI time series with rigid motion

We create an fMRI time series by making M copies of our phantom (i.e., copies of only the object description, not of the simulated image volume), where M is the number of volumes desired for the time series. We model activations by modifying the spin density $\rho(\mathbf{r})$ within anatomically specified ROIs at each time point according to a pre-defined time course, incorporating the appropriate hemodynamic response based on a block paradigm [3]. Both random and correlated motion is modeled from real fMRI data [3] and are applied to the phantom at each point in the time series before simulating the images.

2.5 Effects of field inhomogeneity and motion

The static-field inhomogeneity is determined by the spatial distribution of magnetic susceptibility relative to the direction of the impressed static-field, B_0 [22;23]. In order to show the necessity of field map recalculation when the head is in different orientations, we calculated two different field maps with the head of the subject in differing orientations. For comparison, we also simply rotated the field map from orientation 1 to orientation 2. Figure 2 shows a comparison between the rotated field map of a head and the field map of the equivalently rotated head. As pointed out by Jezzard et al. [23] and Andersson et al. [22], the maps are not the same, as shown by the difference shown in Figure 2 (c). This difference demonstrates that it is not accurate simply to rotate and translate the field map associated with one image and use it to approximate the induced field inhomogeneity map for other images of the rotated and translated head.

3. Experiments and Results

In this section, we present results of the validation of our fMRI phantoms. Figure 3 shows a binary image representing an example air-tissue model, where zero represents air and one

represents tissue, including bone. The inclusion of bone with soft tissue gives only an approximate susceptibility distribution of a human head, but seems to give a sufficiently accurate field map for our purposes. This air-tissue model is used to calculate a field map. The calculated map is compared with the field map acquired from the same subject experimentally in Figure 4. The green line outlines the contour of the brain tissues. Despite the inclusion of bone with soft tissue in our model, we can observe strong similarities between calculated field map and measured field map. It can also be seen that the strongest variations are induced primarily by the sinuses.

The field map, the distribution of spin density, T1, T2*, and the imaging parameters are input to the simulator to produce a volume image. Figure 5 shows a comparison of that simulation to a real image of a human head for a single-shot GE-EPI, which is the typical acquisition method of fMRI. The imaging parameters are as follows: TE/TR = 35/1988.3 ms, a 128×128 imaging matrix and FOV = 24 cm, 28 slices of thickness 4.5 mm with phase-encoding bandwidth of 3698.2 Hz and a flip-angle of 79 degrees. Figure 5 (a) is the simulated image with susceptibility artifacts turned off, (b) is the simulated image with susceptibility artifacts turned on, and (c) is the real EPI image from a Philips 3T MR scanner. For EPI acquisitions, because of the relatively short time spent traversing k -space in the readout direction, geometrical distortion is confined almost entirely to the phase-encoding direction, which in these figures is vertical. Because there is no refocusing RF pulse, intravoxel dephasing is present, leading to reduced intensity in some regions and complete drop-out of intensity in others. Dephasing is most prominent near sinuses at the air-tissue interface, as in the anterior portion of the slices shown in Figure 5. Our results demonstrate that our simulation captures both the typical T2* contrast and susceptibility effects seen in real GE-EPI images.

In addition to static volumes, we created fMRI time series with modeled motion, and with activations of different levels that are chosen arbitrarily based on a block paradigm design, as described in Section 2.4. Three datasets were generated to study the interactions of motion and distortion. The first dataset has susceptibility artifacts turned off and thus exhibits no distortion. We label this dataset “distortion - free”. The second dataset has susceptibility artifacts fixed with the head, which means the magnitude of the distortion of each image voxel depends only on the position of that voxel relative to the head and the direction of that distortion is fixed with the head coordinate system. Thus, while each volume in this dataset is distorted relative to the corresponding volume in the distortion-free data set, the distortion is “static”. There is no distortion of one volume relative to another within the dataset. The first distorted volume is merely rotated and translated to produce subsequent volumes in the static-distortion time series. We label this dataset “static-distortion”. The field maps for each image in the third dataset were each calculated on the basis of the orientation and position of the head at each time point and the distortion was calculated at each point on the basis of the map and the scanner coordinate system. We label this latter data set “updated-distortion”. These three datasets were subjected to motion estimation and functional statistical analysis using SPM2[24].

Figure 6 shows two of the estimated motion parameters for these datasets. The motion sequence we chose for our analysis is one in which there is a relatively large component of

rotation (more than 2 degrees). We chose this data set because, as pointed out in Section 2.5, rotation produces the effects that we are investigating. The solid line refers to the distortion-free dataset, dotted lines to the static-distortion dataset, and dashed lines to the updated-distortion dataset. The motion parameters estimated from the distortion-free dataset are close to true motion. We can therefore use them as a reference. We find that the estimated motion from the static-distortion dataset is very similar to that of the reference. This similarity indicates that static-distortion has little effect on the estimation of motion parameters in fMRI in the time series. In contrast, the estimated motion of the updated-distortion dataset is a poor match to the reference. Figure 6 shows the effect. In that figure, two of the six estimated motion parameters—the rotation angle about the x-axis and translation in the y direction—are each plotted versus time-point for the three cases—distortion-free (solid line), static-distortion(dotted line) and updated-distortion (dashed line). The parameters for the static-distortion case are almost identical to the reference. The similarity is to be expected because in each case the motion is rigid and identical. It is not surprising that the estimate of rigid motion found by SMP2 is the same for each. For the updated-distortion case, however, after correctly following the reference for thirty-one time points, the SPM2 estimate diverges dramatically from the correct motion and never recovers.

There are two likely reasons for this deviation. First, the difference in image distortion between the static and dynamic distortion models happens to increase more rapidly after time-point 31 than before. The difference can be seen as a function of time in Figure 7, which shows a series of snapshots of the difference between the static-distortion volume and the updated-distortion volume corresponding to time points 1, 11, 21, 31, 41, 51, 61, and 71. These are correctly registered volumes (based on the known motion), yet because of warping the registered volumes are different. As can be seen, the difference increases with time. This difference is to be expected, as we have pointed out, because of the change in inhomogeneity caused by rotation, but there is a more pronounced difference for the time points from 41 through 71 than for the points from 1 to 31, indicating a more pronounced warping after time-point 31.

Second, the registration method used by SPM2 to determine the motion parameters is, like all intensity-based methods, subject to the well known problem of the “local optimum” [25;26]. That problem arises because the algorithm searches iteratively for the motion parameters that optimize a cost function (SPM2 uses the mean-square difference in image intensities). Because it is infeasible to perform an exhaustive search, the algorithm may fail to find the global optimum, and may instead get trapped at an erroneous local optimum instead. SPM2 attempts to register each volume to a single “reference volume”, which in our experiment and in the SPM2 default case, is the first volume. It begins its search from the zero-motion position and is thus more likely to find the correct solution when the true motion is closer to zero. The algorithm is successful throughout the time series for both the distortion-free and the static-distortion cases. Thus the algorithm avoids the local-optimum problem for these two cases, but in the dynamic-distortion case the problem is compounded by the pronounced warping of later volumes relative to the first volume, leading eventually (after time-point 31) to entrapment in one or more local optima and to a consequent failure to find the correct motion. When the rotation is quite small, as is the case for the first 31 time points of the time series (Figure 6), the warping of the updated-distortion dataset so

small (Figure 7) that SPM2's algorithm can correctly estimate the motion parameters. As we have pointed out above, however, the updated-distortion dataset suffers from time-dependent warping when the imaged object is rotated, and, as can be seen from the solid line in Figure 6, there is a steady increase of rotation angle about the x-axis (along with an oscillation). With this increased angle comes increased distortion and eventual failure. When the algorithm fails, it confuses motion caused by rotation about x with motion caused by translation in y and finds incorrect values for both parameters. In summary, stronger warping provides a stronger local-optimum challenge to the SPM2 registration algorithm, and it begins to fail dramatically after time-point 31.

The functional analysis performed with SPM2 produces activation maps for the three datasets. In Figure 8 we show the maps of two slices for (a) true activation areas labeled with activation levels. (b) distortion-free (c) static-distortion and (d) updated-distortion datasets. The distortion-free results capture most of the true activations although noise affects them slightly. Not surprisingly, both the static-distortion and the updated-distortion datasets miss some activation in the areas around the sinuses due to loss of signal from intravoxel dephasing. It is interesting to see that there are fewer true positives in the updated-distorted set and the t-value of detected activations is smaller in comparison to the static-distortion set as shown (arrows). The difference between (c) and (d) indicates that updating the distortion degrades the time series, thereby reducing the effectiveness of the activation analysis. Temporal changes in relative position of the activated and nonactivated anatomy are caused by this updating and may be viewed as positional "noise" that may confound the analysis. An idea of the size of the effect and its spatial pattern can be gotten from Figure 9. Here we show a color-encoded map of the temporal standard deviation of the shift in relative position as a function of position for each voxel of one representative slice. The numbers on the color scale at the right are the shift in millimeters. As can be seen, a standard deviation of several millimeters can be observed in some brain regions.

To further quantify the activation analysis, Figure 10 shows an ROC curve for activation analysis performed with SPM2. The area under the curve is somewhat larger for the static-distortion dataset than for the updated-distortion dataset showing that the updated distortion caused an additional amount of difficulty for the analysis package. The difference is not very significant because our current study is based on a block design which is less sensitive to temporal noise. We expect larger difference in studies based on event-related design. This effect will be further evaluated in future studies in order to demonstrate the importance of accounting for it.

4. Discussion and Conclusion

Simulated functional MRI phantoms with real motion and realistic susceptibility artifacts have been presented and analyzed. The simulation was effected by means of an MR simulator tailored specifically to gradient-echo, echo-planar images to simulate fMRI data with controlled and realistic characteristics. The phantom descriptions are obtained from a real anatomical image volume using standard segmentation techniques. A field inhomogeneity map, which is induced primarily by the sinuses, is computed from an air-tissue model. A continuous object is converted into a discrete representation to compute the

signals, and an imaging equation to determine those signals is derived based on solutions to the Bloch equation.

Our model considers not only the image distortion caused by static field inhomogeneity but also the variation in time of the field inhomogeneity map when the human subject moves. Our studies indicate that although the variation is subtle, it has an impact on the analysis of functional MRI studies. Particularly, image distortion and signal loss that vary spatially and temporally in the series result both in inaccurate motion correction and erroneous activation detection. As a result, inaccurate conclusions concerning the effectiveness of analysis techniques may result from experiments based on fMRI phantoms without these effects [3]. Hence, in comparison with previously developed phantoms [3], the phantoms reported on here are expected to provide a better test bed for processing algorithms that are designed to compensate for motion and susceptibility artifacts.

One of the concerns when creating fMRI phantoms using a simulator is the computation time. Hundred of volumes must be simulated to create a new time series. The field map calculation of the method was implemented in C++. The simulator, which takes this map as input and is presented in this paper, was implemented in Matlab (Mathworks, Inc, Natick, MA). At the time of writing, for the updated-distortion phantom, a simulation for one volume requires just over 3 minutes on a 2.0G Hz CPU with 2GB memory, which means that just over five hours is required for a time series with 100 volumes. Because porting the rest of the calculation to a compiled language, such as C++ can be expected to reduce this time significantly, we are in the process of implementing the entire simulation package in C++. There are other avenues available as well. A check of the signal computation in Eq.(4), reveals that the major bottleneck lies in the computation of the first sinc factor

$\text{sinc}\left(\left(\gamma\Delta B_x^{(m,n)}\text{TE}+k_x+k_y\Delta B_x^{(m,n)}/G_y\right)\nu_x/2\right)$, which involves an input argument that is indexed for each object voxel (x_m, y_n) and each point in k-space k_x, k_y . If there are N object voxels within a slice and M^2 points are acquired in k-space, we need $N^2 \times M^2$ inputs to evaluate all these sinc functions. None of the other factors in Eq. (4) involve such a large set of distinct indices, and, as a result, the time required for the calculation of this factor dominates the time required for our simulation. Of course we could ignore this first sinc factor to speed up this computation, but we found image intensity differences up to approximately 15% when this factor is omitted. Another way to reduce the time required is to calculate this factor for only a discretized range of B_x values in order to reduce the N^2 factor to a smaller one. Appropriate discretization levels will, however, depend on the distribution of true B_x values observed in a typical image, which may in turn depend on the application. An additional approach is to employ parallel computing. One can easily run the simulation with multiple processors because the simulation of each volume or even each slice can be performed independently and thus can be executed on different computers with no intracomputer communication required until the end. For example, one time series can be generated within a couple of minutes if 100 processors are available for the calculation. Research will be required to determine optimal levels of discretization and parallelism. Furthermore, the ultimate goal of this project is to build web-distributed software fMRI phantoms. Therefore, most of the computation will be offline work. Thus, phantoms with

typical motion sequence can be pre-generated and available for download. Work is in progress to explore these possibilities.

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Figure 1.

Discretization of phantom. Upper row is the continuous object (gray shading) and continuous static-field inhomogeneity (line plot). Lower row is the discrete object and field inhomogeneity. Within a voxel, the model has a constant spin density, $T1$, and $T2^*$, but the static-field inhomogeneity varies linearly (in x , y , and z) because intravoxel variations of field inhomogeneity are the source of intravoxel dephasing effects.

Figure 2.

Interaction of field inhomogeneity and motion. (a) is the rotated field map. (b) is the field map with rotated head. (c) is (a) minus (b). The unit is Hz. The nonuniformity of (c) reveals the error of simply rotating the field map to approximate the field map induced by a rotated human head. Hence, it is necessary to recalculate the induced field map when considering motion.

Figure 3.

A binary image that represents the air-tissue model is used to calculate the field map. Tissue, including bone, is given intensity 1; air is given intensity 0. Such air-versus-tissue distributions can be approximated, as done here, by segmenting the available MRI data on the basis of a simple threshold.

Figure 4. Comparison of calculated map to measured map. First row is calculated. Second row is measured. Intensity is proportional to magnetic field. Similar field inhomogeneity can be observed at the air-tissue interfaces of both calculated field map and measured one. The green line outlines the contour of the brain tissues.

Figure 5.

Comparison of simulated GE-EPI image with real GE-EPI of human head. (a) Simulated image with static-field inhomogeneity turned off. (b) Simulated image with static-field inhomogeneity turned on. (c) real EPI image. Static field = 3T, TE/TR = 35/1988.3 ms, a 128×128 imaging matrix and FOV = 24 cm, 28 slices of thickness 4.5 mm with phase-encoding bandwidth of 3698.2 Hz and a flip-angle of 79 degrees. The severe distortion (arrows) is caused by static-field inhomogeneity, which in turn is caused by sinuses which are not visible in these slices. Both scalp and skull are omitted from the simulations and have been removed from the real image.

Figure 6.

Difference in estimated motion is observed between dataset with static distortion and dataset with updated distortion. Dotted lines refer to the static-distortion dataset, dashed lines to the updated-distortion dataset, and solid lines to the distortion-free dataset.

Figure 7.

A series of snapshots of the difference images between the static-distortion dataset and the updated-distortion dataset. The images from left to right correspond to time point 1, 11, 21, 31, 41, 51, 61, and 71. The top rows and bottom rows are from two difference slices. As we can see, the difference becomes noticeable for time point 41, which explain the pattern we observe in Figure 6.

Figure 8.

The functional analysis from SPM2 (two slices are shown from top to bottom). (a) true activated ROIs labeled with activation levels. (b) the detected activation maps from “distortion-free” dataset. (c) is the detected activation maps from “static-distortion” dataset. (d) is the detected activation maps from “updated-distortion” dataset. The dissimilarity between (c) and (d) shows that field inhomogeneity that varies dynamically affects the activation analysis.

Figure 9. The temporal standard deviation of the distortion map in millimeters produced by the dynamic component of the distortion in the updated-distortion dataset. This contributes extra temporal noise in fMRI time series not seen in the static-distortion dataset.

Figure 10. ROC analysis on three datasets with different calculated distortions of regions near sinus with 1% signal change. Red line = static-distortion dataset, blue line = updated-distortion dataset, and green line = distortion-free dataset.