Computing Resolution for Neuromagnetic Imaging Systems

Sekihara K*

Abstract
This paper proposes a novel signal-detection-theory-based definition for the resolution of Neuromagnetic imaging systems, and develops a Monte Carlo computer simulation method to compute the resolution. Using the resolution as a performance measure, the performance of various types of sensor hardware is assessed. The assessments include performance improvements due to the increase in the number of sensors and performance changes due to the change in the gradiometer baseline or change in the helmet size. We compare the performance difference between planar and axial gradiometer arrays, and also compare the performance between the conventional radial sensor array and a vector sensor array. We compute the resolution of two existing Neuromagnetic sensor arrays, MEGvision™ (Yokogawa Electric Corporation, Tokyo, Japan) and Elekta-Neuromag TRIUX™ (Elekta Corporate, Stockholm, Sweden).

Keywords
Monte carlo method; Computing resolution; Neuromagnetic imaging systems

Introduction
Electrophysiological activity of neurons in the cerebral cortex generates tiny magnetic fields outside the scalp. Direct non-invasive measurements of this neuronal activity on a sub-millisecond time scale can be achieved by magnetoencephalography (MEG) [1,2]. Modern MEG systems are capable of whole-head coverage with simultaneous measurements by nearly 300 sensors. Such whole-head sensor arrays, together with advanced signal processing algorithms, now enable imaging of dynamic brain activity [referred to as Neuromagnetic imaging [3-5]].

One problem with neuromagnetic imaging is that no clear measure exists for assessing the overall performance of imaging systems. A naive (but very popular) index used for assessing the performance of Neuromagnetic imaging systems is the number of sensors. Although one can imagine that a system with larger number of sensors should have better performance than that of a system with smaller number of sensors, it has been difficult to quantitatively assess the performance improvements due to increasing the number of sensors.

Theoretical assessments of the performance of MEG multi-channel sensor systems have been proposed that apply an information theoretic approach to the sensor data [6]. It may be true that a sensor array that captures a greater amount of information gives higher-quality source images. However, since a quantitative relationship between the information content captured in sensor data and the quality of source images is unknown, such an information theoretic analysis on the sensor data is insufficient for quantitative performance assessments of Neuromagnetic imaging systems.

Resolution expresses a system’s capability to discriminate two closely located sources and has conventionally been used to assess the performance of a wide variety of imaging systems, from classic optical instruments to medical imaging systems including X-ray computed tomography (CT) and magnetic resonance imaging (MRI). However, it is difficult to define the resolution of Neuromagnetic imaging systems because this capability depends on the location and orientation of sources because of the space-variant nature of this imaging method.

Therefore, to assess the resolution of Neuromagnetic imaging systems, some type of Monte Carlo-based method is needed in which the source locations and orientations are randomly chosen in each Monte Carlo trial. This paper develops such a Monte Carlo-based method, which incorporates a novel definition of resolution computed based on the results from Monte Carlo experiments.

Using the resolution, we can explore the relationship between the system’s performance and choices of various hardware design parameters. We can make a quantitative comparison among existing sensor systems and predict the performance of future systems. In Section 4, we describe, in detail, how the resolution for Neuromagnetic imaging systems is defined and computed. Using the resolution as a performance measure, we compare various types of sensor hardware in Section 5. We also compare the resolution of two existing Neuromagnetic imaging systems, MEGvision™ (Yokogawa Electric Corporation, Tokyo, Japan) and Elekta-Neuromag TRIUX™ (Elekta Corporate, Stockholm, Sweden).

Monte Carlo Method for Computing Spatial Resolution

Sensor data generation
We have developed a Monte Carlo simulation method to compute the resolution of Neuromagnetic imaging systems. In this method, we assume two sources that have equal intensity. The locations and orientations of the two sources are randomly chosen in each Monte Carlo trial, with the distance of the sources A fixed across all trials. The locations of the two sources are confined within the simulated brain region shown in Figure 1. A spherical-shell region with outer radius 8 cm and inner radius 1 cm is defined as the brain region and the region more than 4 cm below the sphere center is excluded. The center of the brain region is 10.5 cm below the sensor located at the center of the sensor array.

The two sources have random time courses generated using Gaussian random numbers; the time courses have 4000 time points. One hundred Monte Carlo trials of simulated sensor data are generated, each with random source locations and orientations with a fixed inter-source distance. Gaussian white noise is added to...
Error-bar estimation using bootstrap method

To obtain the confidence interval of the spatial resolution, we use the bootstrap method. Denoting the number of Monte Carlo trials as M, we have M results for $n_D$ and $n_F$, which are denoted $n_D^1, \ldots, n_D^M$ and $n_F^1, \ldots, n_F^M$. In the bootstrap method, we first choose M bootstrap samples from $n_D^1, \ldots, n_D^M$ with replacements, and the bootstrap samples are denoted $n_D^{b1}, \ldots, n_D^{bM}$. We then compute the bootstrap hit rate $H$. We also compute the bootstrap false detection rate $F$ using bootstrap samples $n_F^{b1}, \ldots, n_F^{bM}$ with replacements.
We can now compute the bootstrap $A$-prime using $\hat{F}$ and $\hat{F}'$, and we plot the bootstrap $A$-prime versus the inter-source distance. The resolution, which is the inter-source distance that gives the $A$-prime equal to $a$, is finally obtained. Since there are many ways to choose the bootstrap samples, we can obtain the bootstrap distribution of the estimated resolution and finally obtain the confidence interval of the estimated resolution values by using the bootstrap distribution. We set error bars to the 95% confidence interval in this paper.

**Results of Computing Resolution for Various Types of Neuromagnetic Imaging Systems**

**Resolution computation**

We assume four types of sensor arrays having 80, 160, 320 and 640 sensors for resolution assessment experiments. In these sensor arrays, sensors are aligned on a surface of a spherical helmet that has a 13 cm radius. The sensor locations of these four types of sensor arrays are shown in Figure 2. As shown here, three quarters of the helmet surface are covered by sensors, which are arranged with an equal inter-sensor spacing. In our experiments, the sensor is a first-order axial gradiometer with a 5 cm baseline unless otherwise noted.

We perform the Monte Carlo computer simulation described in the preceding section. Two sets of source reconstruction results are shown as examples in Figure 3. For these results, the two sources are 3 cm apart, and the sensor system with 160 sensors is assumed. Here, Figure 3(a) shows a fairly high signal-to-noise ratio (SNR) (Throughout this paper, the SNR is defined as the ratio between the square root of the power of the generated signal magnetic field and the square root of the power of the noise, which is 50 fT) case (SNR of 2) in which the two sources are detected. A low SNR case (SNR of 0.5) in which the two sources are not resolved is shown in Figure 3(b). Obviously, the $A$-prime metric is equal to one in the first case. It is equal to zero in the second case since the hit rate is zero and the false detection rate is one.

By performing the Monte Carlo experiments with various inter-source distances, the dependence of the $A$-prime metric on the inter-source distance is obtained. Examples of plotting the three metrics, namely the hit rate, the false detection rate, and the $A$-prime metric, with respect to the inter-source distance are shown in Figure 4. The results in Figure 4(a) are obtained using the source intensity set to 60 nAm, which gives an average SNR of 3. In this Figure 4, we can see a clear tendency that the hit rate increases, the false-detection rate decreases, and the resultant $A$-prime metric increases as the inter-source distance increases.

In our computer simulation, the resolution is defined as the inter-source distance that gives an $A$-prime metric of 0.75. In Figure 4, the level of $A = 0.75$ is shown by a horizontal broken line, and the vertical broken line indicates the resolution, which is the inter-source distance giving $A = 0.75$. The plot in Figure 4(a) shows that the resolution in this case is slightly larger than 2 cm and, using the interpolation, the resolution is computed to be 2.1 cm.

The results in Figure 4(b) show an example for a case where the resolution is undefined because the value of $A$-prime never reaches 0.75, even when the intersource distance is as large as 6 cm. These

**Figure 2:** Four types of virtual whole-head sensor arrays with 80 sensors (Top left), 160 sensors (top right), 320 sensors (bottom left), and 640 sensors (bottom right). The filled circles show the sensor locations. Sensors are arranged, with an equal inter-sensor spacing, on three-quarters of the surface of a spherical helmet having a 13 cm radius.
Figure 3: Two sets of examples of source reconstruction results where the two sources are 3 cm apart. Maximum intensity projections of the three-dimensional source power maps onto the transverse, sagittal, and coronal planes are shown, respectively, in the left, middle, and right panels. The contours indicate the relative power of the reconstructed sources. (a) A relatively high SNR case (SNR of 2) where the two sources are resolved. (b) A low SNR case (SNR of 0.5) where the two sources are not resolved. The crosses show the assumed locations of the two sources, and the blank circles in (b) show the location of a detected local peak.

Figure 4: Plots of the hit rate (top), false detection rate (middle), and A-prime metric (bottom) with respect to the inter-source distance. These plots are obtained with the array of 160 sensors arranged on a spherical helmet with a 13 cm radius. (a) The source intensity is set to 60 nAm. (b) The source intensity is set to 6 nAm. The horizontal broken line in the A-prime plot shows the level of $A_p = 0.75$, and the vertical broken line shows the resolution determined as the inter-source distance that gives $A_p = 0.75$. The error bars indicate the 95% confidence interval.
plots were obtained with a source intensity of 6 nAm, which gives an average SNR of 0.3.

Although the adaptive beam former algorithm is used as the source reconstruction algorithm throughout this study, we show the results of attempting to compute the resolution using the sLORETA algorithm [13] for comparison.

Plots of the hit rate, the false-detection rate, and A-prime with respect to the inter-source distance, obtained using sLORETA, are shown in Figure 5. Here, the source intensity is set to 400 nAm, which corresponds to an SNR of 20. This figure shows that, even when the SNR is very high, the A-prime plot never reaches 0.75, and the spatial resolution is not defined under the definition used in this paper.

By repeating the Monte Carlo experiments with different source intensities, a plot of resolution with respect to source intensity can be obtained. Such a plot obtained with an array of 160 sensors is shown in Figure 6. Here, the relationship between mean SNR and source intensity is shown in the lower panel. The source intensity is varied from 4 to 400 nAm. This range corresponds to the SNR range of approximately 0.2 to 20, which is the range encountered in most MEG measurements. In Figure 6, we can see that the resolution is approximately 3 cm for this sensor system when the source intensity is 20 nAm, which gives an SNR of 1. At a very high SNR ratio such as 20, the resolution becomes as small as 1 cm.

Figure 6 indicates that, for the source intensity range between 10 and 100 nAm, the plot of resolution can be regressed by a linear regression model:

\[ \hat{y}(I) = a \log(I) + b, \]  
(7)

where \( I \) indicates the source intensity, and \( \hat{y} \) indicates the modeled resolution (cm) at the source intensity \( I \). The regression coefficients are obtained by least squares fitting to data between 10 and 100 nAm, giving \( a = -3.0 \) and \( b = 7.4 \). The regression results are shown by the broken line in Figure 6. The results indicate that increasing SNR by an order of magnitude improves resolution by 3 cm. In other words, a 3 cm improvement in resolution arises from a 10-fold improvement in SNR.

Note that the linear regression mentioned above was performed for the data in range of 10 and 100 nAm. The source intensity range from 10 to 100 nAm corresponds to the SNR range between 0.5 and 5 according to the bottom panel in Figure 6. This range of SNR is most often encountered in MEG measurements, and thus it is referred to as the practical SNR range in this paper.

**Dependence of resolution on the number of sensors**

We next investigate how the resolution of Neuromagnetic imaging systems depends on the number of sensors. Plots of resolution for the four types of sensor arrays in Figure 2 are shown in Figure 7(a). The plots in Figure 7(a) show a general tendency toward improved resolution when the number of sensors is increased. Although the difference in resolution becomes small under high SNR conditions, there are clear improvements in resolution for the source intensity from 10 to 100 nAm, which corresponds to the SNR range between 0.5 and 5, the practical range of SNR.

To derive a clear quantitative relationship between resolution and number of sensors, we remove the dependence of resolution on source intensity. To do so, the resolution is standardized by that of the 160-sensor array. Let us define the standardized resolution of a \( k \)-sensor system at the source intensity \( I \) as

\[ x_{k}(I) = y_{k}(I)/y_{160}(I), \]

where \( y_{k}(I) \) is the resolution of a \( k \)-sensor system at source intensity \( I \) and \( y_{160}(I) \) is the resolution of the 160-sensor system. Here, \( y_{k}(I) \) is computed using

\[ y_{k}(I) = a(I) + b(I), \]

where \( a(I) \) and \( b(I) \) are the regression coefficients obtained by fitting to data with source intensity \( I \) and number of sensors, \( k \). The plots in Figure 7(a) show a general tendency toward improved resolution when the number of sensors is increased. Although the difference in resolution becomes small under high SNR conditions, there are clear improvements in resolution for the source intensity from 10 to 100 nAm, which corresponds to the SNR range between 0.5 and 5, the practical range of SNR.
intensity $I$. We then apply the linear regression analysis to the standardized resolution data

$$\tilde{x}_{i}(I) = a(k) \log_{10} I + b(k),$$

where $\tilde{x}_{i}(I)$ is the modeled standardized resolution computed using the above equation.

The results of the linear regression are shown by broken lines in Figure 7(b). Here, we see that the dependence of the standardized resolution on source intensity becomes very small but the dependence is not completely removed. We thus further average the standardized resolution over the practical SNR range, such that

$$\beta(k) = \frac{1}{I \in 100} \tilde{x}_{i}(I),$$

where $\{\}$ indicates the average over the region $I \in A$. This mean value of $\beta(k)$, referred to as the effective standardized resolution, is considered to represent the standardized resolution for a sensor system under assessment.

The plot of the effective standardized resolution, $\beta(k)$, with respect to the number of sensors $k$ is shown in Figure 8. The plot shows that there is a relationship between $\log k$ and $\beta(k)$ that is approximately linear when $k$ is less than 300. However, when $k$ becomes greater than 300, the plot starts to deviate from the linear relationship.

We therefore apply a second-order regression model to this plot and the regression results are shown by the broken line in Figure 8; the model fitted to the plot is expressed as

$$\hat{\beta}(k) = 0.37 \log_{10} k^2 - 2.2 \log_{10} k + 4.05,$$

where $\hat{\beta}(k)$ is the modeled effective standardized resolution. The resolution for a given number of sensors can be predicted using Eq. (10). For example, this equation gives $\hat{\beta}(64) = 1.28$ and $\hat{\beta}(320) = 0.86$, so the increase in the number of sensors from 64 to 320 attains a 50% resolution improvements. However, it also gives $\hat{\beta}(640) = 0.785$ and $\hat{\beta}(1000) = 0.774$. The results indicate that, even if we increase the number of sensors from 640 to 1000, the improvement in the resolution is only 1%.

### Resolution dependence on the helmet radius

The analysis described so far assumes that sensors are arranged on a surface of a spherical helmet with a 13 cm radius. Existing SQUID-based whole-head sensor systems have values more or less similar to 13 cm for the radius of their helmets, although their helmets are not exactly spherical. Requirements for the thickness of the helium
dewar wall may result in similar helmet sizes. However, due to the recent development of non-SQUID-type room temperature sensors, it may be possible to develop a whole-head sensor system with a helmet having a much smaller radius. Therefore, the dependence of resolution on helmet size is next investigated.

We compute the resolution of arrays with 80, 160, 320 and 640 sensors for helmet radii of 11.5 cm and 10 cm. (The resolution for the helmet radius of 13 cm was computed, and the results are shown in Figure 7). In Figure 9, the plots for the 160-sensor system are selectively shown. A general tendency for a smaller helmet system to...
give better resolution can clearly be seen in this figure. The resolution values are then standardized by using the values of the 160- sensor system with the helmet size of 13 cm. That is, defining the raw resolution value of the \( k \)-sensor system and the helmet size of \( R \) as \( y_{,k,R}(I) \), the standardized resolution is computed using

\[
\hat{x}_{,k,R}(I) = \frac{y_{,k,R}(I)}{y_{160,13}(I)}.
\]

(11)

The same linear regression analysis as described in the preceding subsection is applied to \( \hat{x}_{,k,R}(I) \) to derive the modeled standardized resolution \( \hat{x}_{,k,R}(I) \). Figure 10 shows the raw resolution plots for 80-, 160-, 320-, and 640-sensor systems in the top panels. The bottom panels show the results of the modeled standardized resolution analysis.

We next derive the effective standardized resolution \( \beta(k, R) \) by using \( \beta(k, R) = \left\{ \hat{x}_{,k,R}(I) \right\}_{I=13}^{50} \). The effective standardized resolution is plotted with respect to the number of sensors in Figure 11. Here, the effective standardized resolution for the each of the three helmet sizes is plotted. The observation that these three plots are nearly parallel suggests that the resolution improvement due to the use of a smaller helmet is nearly independent from the number of sensors. To check this point, the effective resolution \( \beta(k, R) \) is further normalized by the corresponding value when the helmet size is 13 cm. That is, the normalized effective resolution, \( \hat{\beta}(k, R) \), is obtained by using \( \hat{\beta}(k, R) = \beta(k, R) / \beta(k, R = 13) \), and the results are shown in Table 1.

The results in Table 1 were analyzed by two-way analysis of variance (2D-ANOVA) with the level of significance set to 0.005. The analysis indicates that the dependence of \( \beta(k, R) \) on the number of sensors \( k \) is not statistically significant but the dependence on helmet radius \( R \) is statistically significant. Therefore, the mean values obtained by averaging \( \hat{\beta}(k, R) \) over \( k \) should represent the dependence of resolution on helmet size. Table 1 shows that compared to the case of the 13-cm helmet, nearly 20% and 35% resolution increases are respectively attained if we use sensor helmets with radii of 11.5 cm and 10 cm.

Resolution dependence on gradiometer baseline

We assess the effects of gradiometer baseline on resolution. Note that an axial gradiometer with a baseline of 5 cm has been assumed in our analysis presented so far. We here compute the resolution of 80-, 160-, 320- and 640-sensor systems with axial gradiometers baseline \( B \) of 1.6 cm, 3.2 cm, 5.0 cm and \( \infty \) cm (A gradiometer with \( B=\infty \) indicates the magnetometer). Results are shown in Figure 12. Here, the helmet radius is fixed at 13 cm. In this figure, we can observe a general tendency for a sensor system with a larger baseline to give a better resolution.

To make quantitative assessments on this tendency, we analyze the effective standardized resolution, i.e., we standardize each resolution value by using the corresponding resolution value when the baseline is 5 cm, and apply the linear regression analysis to obtain the effective standardized resolution. The results are shown in Table 2.

We analyzed the results in Table 2 by 2D-ANOVA with the level of significance set to 0.005. The analysis indicates that the dependence on number of sensors \( k \) is not statistically significant but the dependence on the baseline value \( B \) is statistically significant. The mean values of the effective resolution across \( k \) thus show the dependence of the resolution on the baseline values. According to Table 2, it can be seen that, compared to the 5 cm baseline case, 34% and 11% resolution losses occur if we use gradiometers with 1.6 cm and 3.2 cm baselines, respectively. On the other hand, use of a gradiometer with 5 cm baseline causes only 10% loss of spatial resolution, compared to the use of a magnetometer sensor.

Comparisons between planar and axial gradiometer arrays

We here assess the resolution of planar gradiometer arrays, and compare the resolution with that of axial gradiometer arrays. To do so, we define three orthogonal directions (\( e, f, g \) as shown in Figure 13). The radial direction is defined as the \( e \) direction, and the two tangential directions are defined as the \( f \) and \( g \) directions in which \( f \) and \( g \) indicate the longitudinal and latitudinal directions, respectively.

The planar gradiometer in which the two sensors are aligned in the longitudinal direction is referred to as the \( f \)-gradiometer, and the planar gradiometer in which the two sensors are aligned in the latitudinal direction is referred to as the \( g \)-gradiometer. We also assess the resolution of an "orthogonal gradiometer", which has a pair of the \( f \) and \( g \) gradiometers at the same location. (Note that the orthogonal gradiometer configuration is used in Elekta-Neuromag TRIUX\textsuperscript{TM}). Since a planar gradiometer with a large baseline is physically infeasible, we assess planar gradiometers with a 1.6 cm baseline and with a 3.2 cm baseline.

We compute the resolution of the \( f \)-gradiometer array, \( g \)-gradiometer array, and orthogonal gradiometer array. The sensor locations are the same as those of the axial 160-sensor array with a
Figure 10: Plots of the resolution (top panel) and modeled standardized resolution $\hat{\beta}_k(I)$ (bottom panel) for arrays of 80, 160, 320 and 640 sensors. (a) Helmet radius of 11.5 cm (b) Helmet radius of 10 cm.

Figure 11: Plots of the effective standardized resolution $\hat{\beta}(k)$ with respect to the number of sensors $k$ for helmet sizes of 10, 11.5 and 13 cm. The plot for the helmet size of 13 cm is the same as that in Figure 8.

Table 1: Normalized effective resolution $\hat{\beta}(k, R)$.

<table>
<thead>
<tr>
<th>Number of sensors, $k$</th>
<th>80</th>
<th>160</th>
<th>320</th>
<th>640</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>helmet radius $R$ (cm)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>11.5</td>
<td>0.83</td>
<td>0.79</td>
<td>0.85</td>
<td>0.78</td>
<td>0.81</td>
</tr>
<tr>
<td>10</td>
<td>0.67</td>
<td>0.63</td>
<td>0.65</td>
<td>0.64</td>
<td>0.65</td>
</tr>
</tbody>
</table>
Figure 12: Resolution plot for the gradiometer baseline equal to 1.6, 3.2, 5 and cm. (The gradiometer with the baseline of cm indicates the magnetometer.) Results for the arrays with 80 sensors, 160 sensors, 320 sensors and 640 sensors are respectively shown in the top-left, top-right, bottom-left, and bottom-right panels.

Figure 13: Schematic view (e, f, g) directions. The unit vector e represents the radial direction. The unit vectors f and g represent the two tangential directions, namely, the longitudinal and latitudinal directions.

Table 2: Effective standardized resolution for four values of gradiometer baseline.

<table>
<thead>
<tr>
<th>Number of sensors</th>
<th>baseline (cm)</th>
<th>1.6</th>
<th>3.2</th>
<th>5</th>
<th>∞</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>1.28</td>
<td>1.06</td>
<td>1.00</td>
<td>0.84</td>
<td></td>
</tr>
<tr>
<td>160</td>
<td>1.37</td>
<td>1.14</td>
<td>1.00</td>
<td>0.91</td>
<td></td>
</tr>
<tr>
<td>320</td>
<td>1.33</td>
<td>1.12</td>
<td>1.00</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>640</td>
<td>1.39</td>
<td>1.09</td>
<td>1.00</td>
<td>0.91</td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>1.34</td>
<td>1.10</td>
<td>1.00</td>
<td>0.90</td>
<td></td>
</tr>
</tbody>
</table>

13 cm helmet radius. Thus, the number of sensors is 160 for the f- and g-gradiometer arrays, and 320 for the orthogonal gradiometer array. The results of computing resolution are shown in Figure 14. The results for the 1.6 cm baseline case are shown in the top panel and those for the 3.2 cm baseline case are shown in the bottom panel. The results for the 160 and 320 axial gradiometer arrays with the same baselines are also shown for comparison.

The results in Figure 14 show that, although the axial gradiometer arrays have resolution significantly better than that of the f-gradiometer alone array and g-gradiometer alone array, the resolution for the orthogonal gradiometer array is better than that of the axial 160 gradiometer array. However, for a fair comparison, the orthogonal gradiometer array should be compared to the axial 320 gradiometer array, whose results are shown by the broken lines. It
can be seen that the resolution of the orthogonal gradiometer array is very close to that of the 320 axial gradiometer array, and this indicates that the performance of the planar and the axial gradiometer arrays with the same baseline is nearly equal when we use the orthogonal gradiometer configuration.

**Effects of vector field measurements on resolution**

We here assess the effects of vector field measurements on resolution. The directions defined by the vectors \((e, f, g)\) are again used, and sensors that measures the magnetic field in the \(f\) and \(g\) directions are respectively referred to as the \(f\)- and \(g\)-sensors. The sensors that measure the magnetic field in the radial \((e)\) direction are referred to as the radial sensors, which have been considered in the preceding subsections. The sensors that measure the magnetic field in all three \((e, f, g)\) directions are referred to as the vector sensors.

We compute resolution of four types of sensor arrays: the radial sensor array, the \(f\) sensor array, the \(g\) sensor array, and the vector sensor array. Here, all types of sensors are assumed to be magnetometers, and the sensors are arranged on a spherical helmet with a 13 cm radius. The sensor locations are the same as those of the 160 sensor array, and thus the number of sensors is 160 for all types of sensor arrays except the vector sensor array, which has 480 \((160 \times 3)\) sensors.

The resolution plots for these four types of sensor arrays are shown in Figure 15. It can be seen in this figure that the resolution of the radial sensor array is significantly better than that of the two types of tangential sensor arrays. Although the vector sensor array attains the highest resolution, the difference between the vector and the radial sensor arrays is small.

To quantitatively assess the resolution differences among these sensor arrays, we apply the standardized resolution analysis where the resolution is standardized using the corresponding values of the radial sensor array. The results of computing the modeled standardized resolution are shown in Figure 16(a). We then compute the effective resolution by averaging the modeled standardized resolution between \(I=10\) and \(100\) nAm. Let us define the effective resolution for the radial, \(f\)-sensor, \(g\)-sensor, and vector sensor arrays as \(\beta_{\text{rad}}, \beta_f, \beta_g,\) and \(\beta_{\text{vec}},\) respectively. The results of computing this effective resolution are...
given in the first line of Table 3. These results indicate that, compared to the use of the radial sensor array, an 80% and 40% resolution losses arise when the $f$- and $g$-sensor arrays are used. The use of the vector sensor array can attain 15% better resolution.

The computer simulation described so far uses the assumption that the radial and tangential sensors are aligned on the same sphere surface with a 13 cm radius. This assumption is somewhat unrealistic for the tangential sensors. Typical sensors in existing MEG arrays are coils with a 2-3 cm diameter. If we use such coils for the tangential sensors, the center of the coil should be arranged 1-1.5 cm above the surface of the helmet. Namely, the tangential sensor array should use a helmet with a radius at least 1 cm larger than the radius of the helmet used for the radial sensor array. This fact should be taken into account when we compare performance between the radial and tangential sensor arrays.

We compute the resolution assuming that the tangential sensors are arranged on a sphere with a radius of 14 cm. The results of computing the modeled standardized resolution in this case are shown in Figure 16(b), and the results of computing the effective resolution are given in the second line of Table 3. These results indicate that the resolution difference between the radial and tangential sensor arrays is as large as 80% for the $g$-sensor array and 140% for the $f$-sensor array. The resolution improvements due to the use of the vector sensor array is less than 10%, despite the vector sensor array uses 3 times more sensors such as 480 sensors in the case of the study described here.

Resolution of existing sensor arrays

We compute the resolution of two types of existing Neuromagnetic imaging systems: MEGvision™ (Yokogawa Electric Corporation, Tokyo, Japan) and Elekta-Neuromag TRIUX™. MEGvision™ has 160 axial gradiometers with a 5 cm baseline [14], and Elekta-Neuromag TRIUX™ has a total of 306 sensors consisting of 102 orthogonal planer gradiometers and 102 magnetometers [15]. Both systems have sensors arranged on a helmet-shaped surface with a radius of approximately 13 cm, although their helmets are not exactly spherical.

The results of computing resolution-source-intensity-SNR plots are shown in Figure 17. Here, to compute SNR, the sensor noise with a standard deviation of 50 fT is again assumed. Here, the plot labeled “Y” indicates the results from MEGvision™. The plot labeled “EL-G” indicates the results from TRIUX in which only the planar gradiometer sensors are used and the plot labeled “EL-G+M” indicates the plot from TRIUX in which both the planar gradiometer and magnetometer sensors are used. The range of the source intensity from 4 to 200 nAm corresponds to the SNR range from 0.3 to 15 for MEGvision™ and 0.2 to 10 for Elekta-Neuromag TRIUX™. The results in Figure 17 show that the resolution of MEGvision™ is almost the same as that of Elekta-Neuromag TRIUX™. However, if only the planar gradiometers are used, the resolution of TRIUXTM is significantly lower than that of MEGvision™ in the practical SNR range (Figures 18-20).

Conclusion

This paper proposes a novel signal-detection-theory-based definition for the resolution of Neuromagnetic imaging systems, and develops a Monte Carlo computer simulation method to compute the resolution. Using the resolution as a performance measure, various types of sensor hardware are compared. We first analyze the performance changes due to change in the number of sensors, and derive an empirical equation that expresses the relationship between
Figure 16: The plots of the modeled standardized resolution, $\hat{\beta}_i(I)$, for the radial sensor array, the g-sensor array, the f-sensor array, and the vector sensor array. (a) Plots obtained under the assumption that the radial and the tangential sensors are aligned on the same spherical helmet with a 13 cm radius. (b) Plots obtained under the assumption that the radial sensors are aligned on a spherical helmet with a radius of 13 cm and tangential sensors on a spherical helmet with a radius of 14 cm.

Table 3: Results of computing effective standardized resolution for radial, tangential, and vector sensor arrays (In this table, Type I sensor arrangement indicates that all types of sensors are arranged on a sphere with a 13 cm radius. Type II sensor arrangement indicates that the radial sensors are arranged on a sphere with a 13 cm radius but the tangential sensors are arranged on a sphere with a 14 cm radius).

<table>
<thead>
<tr>
<th>Type of sensors</th>
<th>$\beta_{\text{eff}}$</th>
<th>$\beta_f$</th>
<th>$\beta_g$</th>
<th>$\beta_{\text{vec}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>type I</td>
<td>1</td>
<td>1.8</td>
<td>1.4</td>
<td>0.85</td>
</tr>
<tr>
<td>type II</td>
<td>1</td>
<td>2.4</td>
<td>1.8</td>
<td>0.91</td>
</tr>
</tbody>
</table>

resolution and number of sensors. We then analyze the influence of the sensor helmet size on resolution, and find that sensor helmets with radii of 11.5 cm and 10 cm, respectively, provide nearly 20% and 35% better resolution than the helmet with a 13 cm radius. We analyze the performance changes due to changes in gradiometer baseline and find that, compared with the 5 cm baseline case, 34% and 11% resolution losses are respectively caused if we use a gradiometer with a 1.6 cm or 3.2 cm baselines. On the other hand, use of a gradiometer with a 5 cm baseline causes 10% loss of spatial resolution, compared to the use of a magnetometer sensor. We find that the planar and axial gradiometer systems attain almost the same resolution. We also compare performances between the radial and vector sensors, and that; the resolution improvement due to the use of the vector sensor array is only 10–15%. Finally, we compute the resolution of two markedly different existing MEG systems, MEGvision™ (Yokogawa Electric Corporation, Tokyo, Japan) and Elekta-Neuromag TRIUX™, (Elekta Corporate, Stockholm, Sweden), and that these two systems have almost the same resolution.
Figure 17: Plots of resolution and SNR versus source intensity for two existing sensor systems. The plot labeled "Y" indicates the results for MEGvision™. The plot labeled by "El-G" indicates the results for TRIUX when only the planar gradiometer sensors are used. The plot labeled by "El-G+M" indicates the results for TRIUX when both gradiometer and magnetometer sensors are used. To compute SNR, we assume sensor noise with standard deviation of 50 fT.

Figure 18: Four scenarios with different $\Delta$ and $V$ settings are shown in (a)-(d) where $\Delta$ is the inter-source distance and $V$ is the size of voxels. (a) A case where the voxel size is greater than $\Delta/2$. (b) A case where the voxel size is equal to $\Delta/2$ and the two sources can be detected. (c) A case where the voxel size is equal to $\Delta/2$ but the two sources cannot be detected. (d) A case where the voxel size is smaller than $\Delta/2$. The locations of the two sources are indicated by filled squares. Voxels are indicated by filled circles. The voxels neighboring the sources are labeled "A", "B", "C", and "D". (e) Three-dimensional source and voxel configuration corresponding to the one-dimensional case shown in (c). The two sources are located at the centers of the cubic grids of voxels, and an empty cube exists between the two cubes containing the sources.
Figure 19: (a) Three-dimensional cubic grid of voxels with a source located inside the cube. The source location is indicated by a small rectangle. The distance between the source and one of the voxels is denoted X. (b) Two neighboring cubic grids of voxels with a source located at the center of the lower cube. The source location is indicated by a small rectangle. The voxel that is nearest the source but belongs to the upper cube is marked with a triangle, and the distance between this voxel and the source is denoted Y.

Figure 20: The concept of A-prime in which the area under the ROC curve is approximated by a rectangle whose corner’s coordinates are defined by (0,0), (H,F), (1,1) and (1,0).

Acknowledgement

This work was supported by a Grant-in-Aid from the Japanese Ministry of Education, Culture, Sports, Science, and Technology (No 26282149) and by a grant from Konika-Minolta Corporation. The author is grateful to Ei Hiyama and Ryo Koga for their dedication in data analysis.

References
