How reliable are the functional connectivity networks of MEG in resting states?

Seung-Hyun Jin,1,3 Jaeho Seol,1,2 June Sic Kim,1,3 and Chun Kee Chung1,2,3

1MEG Center, Seoul National University Hospital, 2Interdisciplinary Program in Cognitive Science, and 3Department of Neurosurgery, Seoul National University, Seoul, Republic of Korea

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Abstract

How reliable are the functional connectivity networks of MEG in resting states? J Neurophysiol 106: 2888–2895, 2011. First published August 31, 2011; doi:10.1152/jn.00335.2011.—We investigated the reliability of nodal network metrics of functional connectivity (FC) networks of magnetoencephalography (MEG) covering the whole brain at the sensor level in the eyes-closed (EC) and eyes-open (EO) resting states. Mutual information (MI) was employed as a measure of FC between sensors in the theta, alpha, beta, and gamma frequency bands of MEG signals. MI matrices were assessed with three nodal network metrics, i.e., nodal degree (Dnodal), nodal efficiency (Enodal), and betweenness centrality (normBC). Intraclass correlation (ICC) values were calculated as a measure of reliability. We observed that the test-retest reliabilities of the resting states ranged from a poor to good level depending on the bands and metrics used for defining the nodal centrality. The dominant alpha-band FC network changes were the salient features of the state-related FC changes. The FC networks in the EO resting state showed greater reliability when assessed by Dnodal (maximum mean ICC = 0.655) and Enodal (maximum mean ICC = 0.604) metrics. The gamma-band FC network was less reliable than the theta, alpha, and beta networks across the nodal network metrics. However, the sensor-wise ICC values for the nodal centrality metrics were not uniformly distributed, that is, some sensors had high reliability. This study provides a sense of how the nodal centralities of the human resting state MEG are distributed at the sensor level and how reliable they are. It also provides a fundamental scientific backdrop for continued examination of the resting state of human MEG.


Introduction

There is an explosion of interest in the resting state FC network research using graph theory. With healthy volunteers, complex human brain FC networks were reported at rest and during finger movement tasks by means of magnetoencephalography (MEG) (Bassett and Bullmore 2006) and electroencephalography (EEG) (Jin et al. in press). In addition, the FC network changes were the salient features of the state-related FC changes. The FC networks in the EO resting state showed greater reliability when assessed by Dnodal (maximum mean ICC = 0.655) and Enodal (maximum mean ICC = 0.604) metrics. The gamma-band FC network was less reliable than the theta, alpha, and beta networks across the nodal network metrics. However, the sensor-wise ICC values for the nodal centrality metrics were not uniformly distributed, that is, some sensors had high reliability. This study provides a sense of how the nodal centralities of the human resting state MEG are distributed at the sensor level and how reliable they are. It also provides a fundamental scientific backdrop for continued examination of the resting state of human MEG.
a study done by Deuker et al. (2009) using binary graphs, we used weighted graphs defined by MI without thresholding. MI matrices were assessed with three nodal network metrics, i.e., nodal degree (Dnodal), nodal efficiency (Enodal), and normalized betweenness centrality (normBC), and then the intraclass correlation (ICC) values were calculated as a measure of reliability.

**MATERIALS AND METHODS**

**Participants.** Ten right-handed healthy subjects (28.0 ± 3.7 yr, mean ± SD; 4 males), who had no neurological problems, voluntarily participated in this study. One participant was excluded from the analysis because she did not finish the study; consequently, MEG signals acquired from nine participants were used for the analysis.

MEGs were recorded twice per participant at the EC and EO resting states for 2 min each. The mean interval between the two recordings was 15 days (SD: 8.4 days) with a range of 7–29 days according to the participants’ availability. The times for the second session were scheduled at the same times as the first measurements for each participant to take into account their circadian rhythm. The protocol was approved by the Institutional Review Board, and all participants gave written informed consent. Handedness was tested using the Edinburgh Handedness Inventory (Oldfield 1971). Part of the data is also being used for a study of the spatial distribution of spectral powers (unpublished), different from the current analysis.

**Data acquisition and preprocessing.** Magnetic fields were recorded inside a magnetically shielded room using a 306-channel whole head MEG system (VectorView; Elekta Neuromag, Helsinki, Finland). MEG sensors are arranged in triplets of two orthogonal planar gradiometers and one magnetometer at 102 locations. Signals were analog filtered between 0.1 and 200 Hz at a sampling frequency of 600.62 Hz. Head movements were tracked with four additional head position indicator coils attached to the heads of the participants. Sixty channels of EEG using the international 10-20 system referenced to the linked ear electrodes, electrooculogram (EOG), and electrocardiogram (ECG) were simultaneously acquired to monitor the participants’ condition. Recordings were done with a participant placed in a supine position with relaxed, and the EC and EO states for 2 min each were continuously recorded per session. Participants were asked to fixate their eyes on a “cross” mark attached on the ceiling in the EO state and to relax and not think about anything during recording.

For removing magnetoencephalographic artifacts, the temporal signal space separation (tSSS) method (Taulu and Hari 2009) implemented in the Maxfilter software (Elekta Neuromag) was used before any analysis was applied. This method was successfully used in a study looking at corticospinal coherence in patients with Parkinson’s disease with a deep brain stimulator implanted (Park et al. 2009), which suggested the feasibility of the tSSS method for artifact removal. Besides tSSS, no additional corrections for eye blinks, muscle, and cardiac artifacts were applied. Epoching was done with Graph software (Elekta Neuromag) after applying tSSS. To ensure participants were in the EC or EO state, EEG signals were visually inspected, especially with the two representative O1 and O2 channels located in the occipital lobe. For the EO state, we tried not to take the signals having excessive eye blinking to minimize the artifact. Finally, we manually took 5 epochs of 10 s each out of the continuous signal. We applied the FieldTrip software package (http://www.mnml.nl/fcdonders/fieldtrip/; Oostenveld et al. 2011) for bandpass filtering of the data. Unless otherwise stated, MEG signals used for the analysis refer to those acquired from the 102 magnetometer sensors.

**Estimation of FC.** We estimated MI values of the bandpass-filtered time series to create an association matrix between MEG sensors. MI as a FC measure has been used in previous studies (Bassett et al. 2006, 2009; David et al. 2004; Jin et al. in press). MI was calculated using the following equation:

\[
MI = MI_{XY} = MI_{YX} = MI[X(t), Y(t)] = -\sum_{X,Y \in O} p[X(t), Y(t)] \log \frac{p[X(t), Y(t)]}{p[X(t)]p[Y(t)]}
\]

where \(p[X(t), Y(t)]\) is the joint probability density function (PDF) between the two time series \(X(t)\) and \(Y(t)\). Thirty-two bins for the construction of the approximated PDF were adopted for 4,096 samples. Maximum MI was 5 bits, since we took the logarithm with base 2. In addition, a corrective term was added when calculating MI to compensate for the effect of finite data and quantization on the PDF as proposed by Roulston (1999). MI matrices of each epoch and frequency band were calculated, and then 5 MI matrices were averaged for the following estimation of graph theoretic measures.

**Nodal network metrics to assess nodal centrality.** For network analysis, weighted and undirected graphs from the MI matrix were evaluated to overcome a shortcoming of a study done by Deuker et al. (2009) using binary graphs. Binary graphs can be indicative of existence of connections, whereas weighted graphs can be used to indicate the strength of connections (Reijneveld et al. 2007). According to previous studies (Barrat et al. 2004; Barthelemy et al. 2005; Newman 2004; Onnela et al. 2005; Park et al. 2004; Stam et al. 2009), weighted graphs can be more accurate models of real networks.

Basically, \(G\) is the set of all nodes and \(n\) is the number of nodes. The total number of nodes was 102, corresponding to the number of magnetometers. The links between two nodes, \(i\) and \(j\), are associated with the connection weights \(w_{ij}\). The normalized weights such that \(0 \leq w_{ij} \leq 1\) for all the nodes (Rubinov and Sporns 2010) equivalent to the MI matrix normalized by the maximum value were used for the following analyses. The shortest weighted path length of the path from node \(i\) to node \(j\), the so-called \(d_{ij}^*\), was calculated as

\[
\sum_{w_{ij} \in E} f(w_{ij}) = \sum_{w_{ij} \in E} \log \frac{g_{ij}}{g_{-ij}}
\]

with the connection weights \(w_{ij}\).

Enodal can be defined as the inverse of the harmonic mean of the shortest path length between a node \(i\) and all other nodes in a network (Achard and Bullmore 2007). It is regarded as a measure of the communication efficiency (Wang et al. 2009). It is derived from the following equation:

\[
Enodal(i) = \frac{1}{n-1} \sum_{j=1, j \neq i}^{\left|\text{nodes}\right|} \frac{1}{d_{ij}^*}
\]

BC is defined as the fraction of all the shortest paths in the network that pass through a given node (Rubinov and Sporns 2010). Thus it measures how often nodes occur on the shortest paths between other nodes (Buckner et al. 2009). It is defined as the following equation:

\[
BC = \sum_{k,h \in \text{nodes}} \frac{g_{kh}(i)}{g_{kj}}
\]

where \(g_{kh}\) is the number of shortest paths between nodes \(h\) and \(j\), and \(g_{kh}(i)\) is the number of shortest paths between nodes \(h\) and \(j\) passing through \(i\). Note that BC is computed equivalently on either binary or weighted graphs, but the shortest path length is derived from relevant binary or weighted paths. BC is normalized by the mean value of BCs.
in a network (He et al. 2008; Wang et al. 2010), so afterwards we denote it as normBC.

Extraction of the shortest path length from a weight matrix and calculation of each nodal network metrics were obtained with functions from the Brain Connectivity Toolbox (http://www.brain-connectivity-toolbox.net/). When necessary, the scripts were modified.

Each nodal network metric was standardized by converting to Z scores for the condition before group averaging to reduce intersubject variability. The conversion to Z score does not affect the topography of the individual subject maps but does cause the values in each subject map to be comparably scaled (Buckner et al. 2009).

Reliability test. As a measure of test-retest reliability for each centrality estimate, we calculated a sensor-wise ICC value, which has widely been used for the reliability test (Deuker et al. 2009; Shehzad et al. 2009; Zhang et al. 2011). The ICC value for consistency measurements was based on a two-way random effect model (McGraw and Wong 1996), and it was calculated according to the following equation to assess the reliability of a single measure [ICC (2,1)]:

$$ ICC(2,1) = \frac{MS_s - MS_e}{MS_s + (k-1)MS_e}, $$

where $k$ (in this case, with a value of 2) is the number of measurements per subject. $MS_s$ and $MS_e$ indicate a between-subject mean square and error mean square, respectively. The ICC is close to $+1$ if the measurements made in the two MEG sessions are consistent on repeated recordings for each subject in the sample. In the case of a negative ICC value, we set it to 0, meaning completely nonreliable, as generally suggested (Kong et al. 2007; Zhang et al. 2011), since such a situation is theoretically impossible (Rousson et al. 2002). Following the criteria proposed by Cicchetti and Sparrow (1981), each ICC value was categorized into a value of $>0.75$ as "excellent" reliability, 0.59–0.75 as "good," 0.40–0.58 as "fair," and $<0.40$ as "poor."

Statistical analysis. Statistics were done using multivariate analysis of variance (MANOVA) models to examine the normalized MI differences between the two resting states and among frequency bands simultaneously. For each frequency band, normalized MI values were averaged across all possible sensor pairs, thus yielding one average MI per condition per subject. MANOVA was implemented in SPSS (version 18) with a significance level of 0.05. All data are given as means ± SD. Before MANOVA was applied, normality of the variables was assessed using the Lillifors test implemented with the statistics toolbox in MATLAB. A paired t-test was performed to see whether there were statistical differences of ICC values over sensors for nodal network metrics between two states at each frequency band.

Visualization. pajek software (http://vlado.fmf.uni-lj.si/pub/networks/pajek/) was employed for the network visualization of the FC network. The scalp plotting program used in the present study was adapted from "headplot" MATLAB script (Delorme et al. 2007).

RESULTS

Figure 1 displays the average MI values for each frequency band and state. There was a trend for difference between the EC and EO states in the first session ($F_{1,67} = 3.067, P = 0.084$; Fig. 1A), but no significant difference was found in the second session ($F_{1,67} = 0.970, P = 0.328$; Fig. 1B). However, there was a significant difference between the bands (1st session: $F_{3,67} = 246.871, P < 0.0001$; 2nd session: $F_{3,67} = 360.875, P < 0.0001$), meaning the average strength of FC decreased as the frequency increased. No significant interaction between the state and band was found.

To visualize state-related changes, FC network differences between the EC and EO states at each band are shown in Fig. 2 (left, greater connectivity in the EC state than in the EO state; right, greater connectivity in the EO state than in the EC state). To achieve this, the group-averaged, normalized MI matrices at each band and at each condition were thresholded by the corresponding mean ± SD value of all the subjects. Note that the thresholding is done only for visualization. Otherwise, the network could not be recognizable due to too many connections. Next, the thresholded group-averaged FC networks in the EO state were subtracted from those in the EC state. Many connectivity changes in all four frequency bands were observed. It seems that more connections were involved in the EC state. As for the connection strength, the alpha-band FC network had stronger connectivity in the EC state over the bilateral temporal regions and parietal regions including the long-range interhemispheric connections. During the EO state, more posterior connectivities were observed than during the EC state across the frequency bands. An important point inferred from Fig. 2 is that drastic state-related network changes were involved in between the two resting states, regardless of the fact that there was no significant difference in the average MI between the two resting states, as described above.


Figure 2. Graphical representations of the functional connectivity (FC) network state-related changes (1st session) from the EC to EO state at each frequency band. Grand-averaged MI matrices at each frequency were thresholded by a mean + SD MI value of all the channels across the subjects. Left column shows greater connections in the EC state than in the EO state, and right column indicates greater connections in the EO state than in the EC state (L, left side; R, right side).

Figure 3 represents the whole head spatial distribution of the group-averaged nodal network metrics at each frequency band, metric, and state. The second rows of each sub-box demonstrate subjectwise differences between two sessions of nodal network metrics.

Topographic maps estimated by Dnodal and Enodal metrics are similar to each other at each frequency band, and overall, normBC maps look to be distinct from the maps evaluated with Dnodal and Enodal. As for statewise differences, slight changes were revealed in the theta, beta, and gamma bands, whereas relatively considerable changes were seen in the alpha band. Apparently, the second rows of each sub-box in Fig. 3 represent some sensors having a large variance between two sessions, which others did not have. A more precise investigation on the consistency of the nodal network metrics was done with the following ICC estimation.

Group-averaged sensorwise ICC values with means ± SE are listed in Table 1. The mean and SE for each subject were calculated over the channels and averaged over the subjects. Reliability of the nodal network metrics varied depending on the bands and metrics. The percentage of sensors with ICC values ≥0.4 versus the total number of the sensors is also shown in Table 1.

As for Dnodal, the beta band showed good to excellent reliability with a mean of 0.615 (EC) and 0.655 (EO). The ICC values for the theta and alpha bands indicated fair to good reliability. On the other hand, the gamma band presented poor reliability. A significantly higher reliability of the alpha band in the EO state than in the EC state was found (P < 0.001). The beta band showed a trend for a difference (P = 0.068). The percentage of sensors showing fair reliability ranged up to 90%.

In the case of normBC, the highest mean for ICC was 0.426, corresponding to a fair reliability; therefore, the ICC values ranged from poor to fair level. However, the percentage of sensors showing fair reliability in the alpha band was 87 and 79% in the EC and EO states, respectively. This means that sensorwise ICC values largely fluctuated.

Regarding Enodal, fair to good reliabilities were observed in the theta, alpha, and beta bands. Again, poor reliabilities were found in the gamma band with a mean of 0.347 in the EC and 0.359 in the EO states. High ICC values in the EO state compared with the EC state were also noticeable (P < 0.001). The percentage of sensors showing fair reliability ranged up to 97%.

Figure 4 depicts the spatial ICC distributions for both states at each frequency band. Sensors exhibiting an ICC ≥0.4, corresponding to an ICC above the fair reliability, were rendered on a scalp surface. It is easily recognizable that nodal ICC values varied between different nodes and metrics. Figure 4 also implies that even in the case of the beta band in the EC state showing the best mean ICC value as presented above, some sensors look less reliable than other sensors. The mean ICC values in the gamma band were below 0.40, referring to a poor reliability, but the nodes over the parietal regions with the Dnodal metrics displayed high ICC values. Together, the values indicate that the reliability of nodal network metrics seems to have a large amount of fluctuation between regions.

**DISCUSSION**

We examined the issue of how reliable the nodal network metrics of FC networks of MEG at the sensor level are in the EC and EO resting states with healthy volunteers in a hypothesis-free manner. We observed that the test-retest reliabilities of resting states ranged from a poor to a good level depending on the bands and metrics used for defining the nodal network characteristics. The FC networks in the EO resting state showed greater reliability when assessed with Dnodal and Enodal metrics than with normBC. The gamma band networks were less reliable than the theta, alpha, and beta networks across the nodal network metrics. This study is important in terms of understanding how the nodal network centralities of the human resting states in MEG are distributed at the sensor level and how reliable they are depending on the EC and EO resting states across frequency bands, which has never systematically been addressed. Our results showed the state/frequency-dependent network reorganization, nodal centrality, and reliability distributions.

State-dependent properties. The result that each frequency band represented distinct FC patterns (Fig. 2) suggests frequency-specific network reorganization, which may imply different...
functional roles of each frequency band in the face of the changing resting states. The most salient feature of the state-related FC network reorganization was found in the alpha band. As shown in Figs. 3 and 4, nodal centrality and reliability distributions are different depending on the states. Especially, the alpha-band network displayed the most salient changes in nodal centrality distributions, which could be expected from the network reconfiguration results of Fig. 2. As for reliability, it was observed that the alpha band in the EO resting state had a higher reliability than in the EC resting state. This implies that the alpha band in the EO resting state presents a more stable network configuration than in the EC resting state. It is obvious that both the EC and EO states are the resting state in which no task is conducted, which is clarified by the result that there was no significant difference in the average MI difference between the EC and EO states. However, the EO resting state is associated with nonspecific or non-goal-directed visual information gathering (Yan et al. 2009).

Table 1. Mean ICC values for each frequency band at both eyes-closed and eyes-open resting states

<table>
<thead>
<tr>
<th>Metric</th>
<th>Band</th>
<th>Eyes-Closed</th>
<th>Eyes-Open</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dnodal</td>
<td>Theta</td>
<td>0.484 ± 0.078 (65)</td>
<td>0.504 ± 0.086 (70)</td>
</tr>
<tr>
<td></td>
<td>Alpha</td>
<td>0.473 ± 0.088 (65)</td>
<td>0.600 ± 0.071† (81)</td>
</tr>
<tr>
<td></td>
<td>Beta</td>
<td>0.615 ± 0.072 (84)</td>
<td>0.655 ± 0.064* (93)</td>
</tr>
<tr>
<td></td>
<td>Gamma</td>
<td>0.298 ± 0.084 (34)</td>
<td>0.315 ± 0.095 (40)</td>
</tr>
<tr>
<td>normBC</td>
<td>Theta</td>
<td>0.256 ± 0.081 (32)</td>
<td>0.272 ± 0.081 (35)</td>
</tr>
<tr>
<td></td>
<td>Alpha</td>
<td>0.426 ± 0.093 (87)</td>
<td>0.383 ± 0.098 (79)</td>
</tr>
<tr>
<td></td>
<td>Beta</td>
<td>0.380 ± 0.092 (52)</td>
<td>0.372 ± 0.084 (53)</td>
</tr>
<tr>
<td></td>
<td>Gamma</td>
<td>0.256 ± 0.067 (26)</td>
<td>0.289 ± 0.085 (33)</td>
</tr>
<tr>
<td>Enodal</td>
<td>Theta</td>
<td>0.499 ± 0.073 (67)</td>
<td>0.517 ± 0.084 (75)</td>
</tr>
<tr>
<td></td>
<td>Alpha</td>
<td>0.474 ± 0.089 (89)</td>
<td>0.604 ± 0.069† (97)</td>
</tr>
<tr>
<td></td>
<td>Beta</td>
<td>0.559 ± 0.082 (75)</td>
<td>0.577 ± 0.073 (78)</td>
</tr>
<tr>
<td></td>
<td>Gamma</td>
<td>0.347 ± 0.087 (45)</td>
<td>0.359 ± 0.096 (41)</td>
</tr>
</tbody>
</table>

Values are means ± SE; values in parentheses indicate the percentage of sensors with intraclass correlation (ICC) values ≥0.4 vs. total number of the sensors (in this instance, 102). Note for ICC value: >0.75, excellent; 0.59–0.75, good; 0.40–0.58, fair; <0.40, poor. *P < 0.1; †P < 0.001, significance level for the comparison of ICC values over sensors between the 2 states. and Enodal metrics (Table 1). This implies that the alpha band in the EO resting state presents a more stable network configuration than in the EC resting state. It is obvious that both the EC and EO states are the resting state in which no task is conducted, which is clarified by the result that there was no significant difference in the average MI difference between the EC and EO states. However, the EO resting state is associated with nonspecific or non-goal-directed visual information gathering (Yan et al. 2009).

Frequency-dependent properties. The result that each frequency band represented distinct FC patterns (Fig. 2) suggests frequency-specific network reorganization, which may imply different functional roles of each frequency band in the face of the changing resting states. The most salient feature of the state-related FC network reorganization was found in the alpha band. As shown in FC network maps in Fig. 3, nodal centrality spatial distributions in the alpha-band FC network in the EC state are different from those in the EO state. The human brain is likely to operate dynamically, facilitating optimal reconfiguration of neuronal assemblies depending on the change of cognitive states induced either externally or internally (Bassett and Bullmore 2006). Thus our result may suggest that the alpha-band FC network seems to be most responsible for responding to the resting state changes with sufficiently reliable consistency. This is conceivable when taking into account the notion that alpha oscillations are the most consistently reported electrophysiological hallmark of sustained alertness (Sadaghiani et al. 2010).
suggestion reliability, were rendered on a scalp surface. The sensors had high centrality, and others did not, which might be challengeable topic.

A common finding across the three metrics was that nodal centrality spatial distributions and ICC distributions of the Dnodal and Enodal looked comparable with each other at each frequency band in both the EC and EO states. Taking into consideration the original meaning of each metric, the nodal centrality features in terms of the connection strength representing FC (Dnodal) and the communication efficiency (Enodal) were similar at each frequency band and state. On the other hand, the nodal centrality spatial distributions estimated with normBC displayed somewhat different patterns. This does not necessarily mean that normBC is not feasible for investigation of nodal network properties, because normBC may provide complementary information as a measure of how often nodes become shortcuts between other nodes, and highly reliable values were observed in some sensors as illustrated in Fig. 4. In fact, normBC has been used as a measure of cortical hub distributions in many studies (Buckner et al. 2009; He et al. 2008; Wang et al. 2010). A common finding across the three metrics was that nodal centrality values were not uniformly distributed, that is, some sensors had high centrality, and others did not, which might suggest sensor-specific roles as a pathway interconnecting sensors in FC networks. Similarly, ICC values were not uniformly distributed.

**Significant MI difference between bands.** No significant difference between the EC and EO states was found. This means that the average strength of the FC did not differ from each other at each frequency band with respect to the change in resting state. A value of MI could be treated as an indicator of coupling information (Jeong et al. 2001; Jin et al. 2006a, 2006b). Thus our result could be interpreted as the overall demand for coupling information in the EC and EO resting states being similar to each other.

However, highly significant differences between the bands, indicating the average MI decreased as the frequency band increased, were consistently observed in both sessions. This implies that the strength of the FC per se in a low-frequency band tends to be stronger than in a high-frequency band. It is congruent with the finding of Bassett et al. (2009) showing decreased MI curves as the frequency band increased in both healthy volunteers and schizophrenic patients at rest. However, it does not necessarily mean that a low-frequency band more efficiently manipulates the network, since Bassett et al. (2009) also revealed maximum cost efficiency tended to increase as a function of frequency. Discussing our findings from a cost-efficiency standpoint is beyond the scope of this study, but it is obvious that there are frequency-related differences in the strength of the FC measured by MI in the resting states.

**Methodological considerations.** One limitation of the present study is the relatively small sample size. However, we emphasize the fact that despite the small sample size, our results had fairly good reproducibility. Another limitation of note is related to the age range and sex differences of the participants. Electrophysiological activities in the brain may vary depending on the age group (Niedermeyer 2005). Although the sex was almost balanced in the present study, the age range of our participants was somewhat wide, from 22 to 35 yr. The last limitation is that this study is restricted to the sensor level. Further source analysis would be helpful in figuring out the issue of which regions are the neuronal generator for each frequency band, which may give a hint to link the frequency-specific FC network and the functional role of each frequency band in the resting state. It should be noted that there might be a possibility that nearby MEG sensors are likely to pick up activity of the same source, which may produce spuriously high connectivity between them, especially at a sensor level (Stam et al. 2009). The time-shift test for volume conduction on information theoretic measures of connectivity proposed by Vicente et al. (2011) and Wibral et al. (2011) could provide a solution for this issue. One issue that is beyond the scope of the present study is to look at the intrinsic types of edges, i.e., direct or indirect link. Further investigation with respect to the effects of types of edges would be a challengeable topic.

In conclusion, to the best of our knowledge, this is the first study on the reliability of nodal network metrics of FC networks in MEG at the sensor level in the EC and EO resting states, which provides a scientific background for continued studies using resting-state FC network based on graph theory. We suggest that nodal network measures in the resting state can be utilized as reliable biomarkers of longitudinal studies. Selection of resting states (EC vs. EO), frequency bands, and

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Fig. 4. Topographic maps of intraclass correlation (ICC (2,1)) values at each frequency band in both EC and EO states. Warmer colors have greater reliability. Sensors exhibiting an ICC >0.4, corresponding to values above the fair reliability, were rendered on a scalp surface.
sensor locations would be crucial factors determining the power of graph theoretic biomarkers.

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DISCLOSURES
No conflicts of interest, financial or otherwise, are declared by the author(s).

AUTHOR CONTRIBUTIONS

REFERENCES


