Talairach-Based Parcellation of Neonatal Brain Magnetic Resonance Imaging Data: Validation of a New Approach

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ABSTRACT

Background and Purpose. Talairach-based parcellation (TP) of human brain magnetic resonance imaging (MRI) data has been used increasingly in clinical research to make regional measurements of brain structures in vivo. Recently, TP has been applied to pediatric research to elucidate the changes in regional brain volumes related to several neurological disorders. However, all freely available tools have been designed to parcellate adult brain MRI data. Parcellation of neonatal MRI data is very challenging owing to the lack of strong signal contrast, variability in signal intensity within tissues, and the small size and thus difficulty in identifying small structures used as landmarks for TP. Hence the authors designed and validated a new interactive tool to parcellate brain MRI data from newborns and young infants.

Methods. The authors' tool was developed as part of a postprocessing pipeline, which includes registration of multichannel MR images, segmentation, and parcellation of the segmented data. The tool employs user-friendly interactive software to visualize and assign the anatomic landmarks required for parcellation, after which the planes and parcels are generated automatically by the algorithm. The authors then performed 3 sets of validation experiments to test the precision and reliability of their tool.

Results. Validation experiments of intra- and interrater reliability on data obtained from newborn and 1-year-old children showed a very high sensitivity of >95% and specificity >99.9%. The authors also showed that rotating and reformatting the original MRI data results in a statistically significant difference in parcel volumes, demonstrating the importance of using a tool such as theirs that does not require realignment of the data prior to parcellation. Conclusions. To the authors' knowledge, the presented approach is the first TP method that has been developed and validated specifically for neonatal brain MRI data. Their approach would also be valuable for the analysis of brain MRI data from older children and adults.

Key words: MRI, brain, newborn, infant, parcellation, Talairach.


The development of brain-mapping techniques using 3-dimensional (3D) magnetic resonance imaging (MRI) led to the need for standardized schemes for regional analysis of brain structure over time and between subjects. Different approaches for parcellating the human brain have been proposed in the literature. However, the scheme presented by Talairach and Tournoux in the form of a coplanar stereotactic atlas using anatomical landmarks became the universal coordinate system for the human brain. Developed initially for stereotactic and functional neurosurgery, this atlas continues to be the most popular coordinate system of the brain in numerous modalities.
Parcellation of neonatal brain MRI data is very challenging owing to a lack of strong signal contrast, variability in signal intensity within tissue classes (eg, due to partial myelination of the white matter), and difficulty in identifying structures such as the AC and PC because of their small size. In addition, the methods used for TP in earlier adult and pediatric studies consist of performing TP by reformatting the MR images to standardize the head position and align the images into “Talairach” or “ideal” space. This reformatting is required because in actual brain MRI data, the position of the brain is usually shifted from the center of the traditional Cartesian system of coordinates. Therefore, the actual axial, midsagittal, and coronal planes are not parallel to the ideal coordinate system. The reformatted images are usually of inferior quality compared with the originals because of interpolation of MRI data. In neonates, where the AC and PC are very small and unmyelinated, interpolation artifacts may lead to difficult and hence inaccurate landmark detection.

A means to perform accurate and precise TP on neonatal brain MRI data is crucial for the elucidation of regional volumetric abnormalities in the brains of newborn infants with early-acquired brain injury. Such measurement of regional tissue volumes will be essential to determine regional structural disturbances resulting from such injury as well as specific structural abnormalities underlying long-term neurodevelopmental sequelae. Such a TP method could also be used to study the adaptive response to injury, that is, plasticity, in the developing brain. In this article, we describe a new approach for TP that does not require any reformatting of the original scans and is designed specifically for volumetric analysis of neonatal and infant brain MRI data. We also present the results of our validation of this method with regard to intra- and interrater reliability, and we compare results obtained from measurement of data in the original position with data obtained using realignment and reformatting of the original data.

Methods

Our approach for TP is part of a pipeline that includes several steps of distant postprocessing procedures, that is, off site from the MRI scanner, following acquisition of high-resolution neonatal and infant brain MRI data.

Image Acquisition

All MRI data were obtained using a 1.5-T scanner (GE Signa, GE Medical Systems, Milwaukee, WI). We acquired 3-channel MRI on the whole brain of infants. The channels consisted of (1) coronal 3D SPGR (Spoiled Gradient Recalled acquisition in the steady state) with voxel...
size 0.703125 × 0.703125 × 1.5 mm³, FOV 180 mm, TE 5, and TR 35 ms, and (2) coronal dual echo images obtained with a conventional spin-echo imaging with voxel size 0.703125 × 0.703125 × 3 mm³, FOV 180 mm, TE 84 and 168, and TR 5000 ms.

Postprocessing Procedures

Registration. The 3 channels of MRI data were registered using an automated registration method based on mutual information.  

Segmentation. A series of image-processing algorithms were used to segment 3D MR images into separate tissue classes: cortical gray matter, subcortical gray matter, unmyelinated white matter, myelinated white matter, and cerebrospinal fluid. These algorithms were designed to classify tissue types based on intensity value in the 3 channels, using a template-moderated classification. This template-moderated classification adds to the statistical classification algorithm an age-matched anatomical template registered to the initial classification. This approach allows classification of tissue class not only according to...
signal intensity but also according to anatomical localization. Thus, anatomically different structures with similar signal intensity characteristics (i.e., subcortical vs cortical gray matter) can be classified correctly using this technique. The combination of these algorithms has proven to be an effective, efficient, and reliable method to segment the brain based on both signal intensity and anatomical information.

Interactive parcellation. Talairach-based parcellation requires definition of the equation of the midsagittal plane and the coordinates of the anatomical landmarks of the AC and PC. These coordinates were determined using the following methods.

Identification of midsagittal plane: We defined an “ideal” midsagittal plane as a virtual geometric plane about which the brain represents maximum bilateral symmetry. Different computational methods are reported for automated extraction of the midsagittal plane. However, the lack of signal contrast in the newborn brain makes these automated approaches less reliable in the newborn. Hence, we used an interactive method for identification of the midsagittal plane. This method allows the user to determine anatomical landmarks of the midsagittal plane by choosing points on any of the coronal, axial, or sagittal sections of the MRI data. A least squares algorithm is used to fit the set of the chosen points to the equation of the desired plane.

Identification of AC and PC: Nowinski et al reported a patent-pending algorithm for AC-PC identification. To our knowledge, no such algorithm has been published for use in the neonatal brain. The main challenge in neonatal MRI is that such an algorithm will not be able to use signal intensity as a primary channel of information for automatic identification of the AC and PC because the commissures are unmyelinated in newborn infants (particularly in premature infants with a gestational age of < 37 weeks). Thus, the AC and PC cannot be easily distinguished from the surrounding white matter and subcortical gray matter. We therefore employed an interactive approach to define the regions of the AC and PC by choosing points visualized on the 3 planes. The coordinates of the AC and PC are then estimated as the centers of mass of the set of determined points. Using the same interactive approach, we also defined an additional point tangent to the GC to define an additional coronal plane passing through this point.

Parcellation algorithm: Based on the equation of the midsagittal plane and the coordinates of the AC and PC, we define, using elementary geometry, the actual axial plane as the plane passing through the AC and PC and perpendicular to the midsagittal plane. The coronal planes were determined as the planes passing through the AC, PC, and GC and perpendicular both to the axial and midsagittal planes. The regions delineated between the planes described above represent the 16 parcels obtained by this Talairach-based parcellation method. Because the planes defined by TP in our approach are generally not parallel to the grid of the MRI scan, some of the voxels are divided into parts that belong to different parcels. Therefore, our algorithm calculates the volume of each parcel as the summation of volumes of voxels that belong totally to the defined parcel and volumes of corresponding parts of voxels that belong partially to that parcel. This decomposition algorithm was then applied to the tissue classification label maps to determine the volumes of each tissue class in each parcel.

Validation

Three sets of validation experiments were performed, aimed at estimating the precision and reliability of our parcellation approach. Each experiment is described in detail below.

Validation on neonatal MRI. To estimate the reliability of our TP on neonates, 4 healthy term-born newborns underwent a brain MRI scan at term age (40 weeks). We applied the segmentation algorithm described above to obtain the tissue classification. Using the implemented interface for our TP approach, 2 experts repeatedly performed parcellation 5 times for each case. The experts were blinded to the identity of the infants and performed the parcellation on different days. We used a novel algorithm for the evaluation of image segmentations, the “Simultaneous Truth and Performance Level Estimation” method (STAPLE), to obtain a reference standard. STAPLE presents an expectation-maximization algorithm for computing a probabilistic estimate of the “ground truth” segmentation from a group of expert segmentations, and a simultaneous measure of the quality of each expert. In this algorithm, the expert segmentation decision at each voxel is directly observable, the hidden ground truth is a binary variable for each voxel, and the quality of each expert is represented by sensitivity and specificity parameters. The process to identify the expert quality parameters and ground truth consists of iterating between estimation of the hidden ground truth given a previous estimate of the expert quality parameters and estimation of the expert quality parameters based on how they performed given the new estimate of the ground truth (see appendix). We applied STAPLE to determine the most likely ground truth of each parcel in all parcellated cases and, at the same time, the corresponding sensitivities and specificities.

Validation on 1-year-old babies. To estimate the contribution of the patient age to overall precision of our approach, the above-described validation experiment was repeated on MRI data obtained from 4 infants scanned at 1 year of age. We applied the same segmentation and validation (STAPLE) methods to evaluate the reliability of the parcellation results obtained in infants of different ages.

Assessment of the effect of reformatting of neonatal MRI data on the parcellation results. A major problem in the analysis of 3D neonatal brain MRI data is that the infant’s head is typically not aligned in the scanner, so that the image data are rotated or tilted away from the ideal or Talairach axes. The MRI data are usually rotated to align the data with ideal space prior to parcellation, resulting in interpolation.
and degradation of the original data. The best way to determine the effect of such reformatting of neonatal MRI data on the resulting parcellation would be to scan an infant repeatedly with different positions of the head inside the scanner and then to reformat the MRI data to match the ideal alignment and perform TP on each of these reformatted data sets. Any significant difference in the volumes of different parcels would reflect the effect of resampling of the original data. We did not use this approach, as it would require excessive scanning time for an unsedated newborn. Thus, to estimate the effect of reformatting, we performed the following experiment.

We used the SPGR images of one of the newborn infants scanned in a position almost perfectly aligned with the Talairach or ideal space. The MRI data were then re-sampled using cubic interpolation 4 times, by rotating by an angle of 1, 2, 3, or 4 degrees along each of the 3 axes. The intracranial cavity mask (generated using the segmentation method described above) was resampled, using nearest neighborhood interpolation in a similar way. An expert performed TP 5 times on this case in each of the 5 positions. STAPLE was then applied to estimate the reference standard and the variability resulting from the change in position and reformatting of the original data.

**Results**

**Description of the TP Procedure and Interface**

A user-friendly interface with a triplanar display was created (Fig 2). The user performs TP based on the methodology described above using the following sequence of steps:

1. The user loads the original 3D grayscale (usually SPGR) image data.
2. The user loads the tissue classification.
3. The user then sets the Talairach landmarks interactively (midsagittal plane, AC, PC, and GC). The interface allows the user to choose points on any of the axial, sagittal, or coronal planes. A point chosen on one plane is automatically shown in its corresponding location on the other 2 planes. This feature allows the user to confirm visually on all 3 planes simultaneously the location of the chosen point (Fig 2). This step thereby improves the accuracy of the designation of small landmarks such as the AC and PC by confirming the location of each point in all 3 planes.
4. The TP algorithm is then run, which decomposes the segmented data into 16 parcels using the segmentation method described above) was resampled, using nearest neighborhood interpolation in a similar way. An expert performed TP 5 times on this case in each of the 5 positions. STAPLE was then applied to estimate the reference standard and the variability resulting from the change in position and reformatting of the original data.
5. The resulting parcel volumes are then saved as a table containing the total volumes of each tissue type for each
The interface automatically generates a corresponding histogram to display these results for visual inspection (Fig 4). This interface has a number of advantages that make it particularly valuable in medical research. First, the computational time is less than 17 seconds (on a Sun workstation Ultra 10) regardless of the number of slices in the 3D volume. Second, it is written in Matlab 6.15, allowing it to work on different operating systems such as Windows, Solaris, and others. Finally, the software algorithm is multifunctional. Although it was developed initially to perform TP to divide the neonatal brain into 16 parcels, it can also perform TP using the classic scheme frequently employed in adult neurological studies by dividing the brain into 12 parcels. Furthermore, the triplanar display and semiautomatic algorithm for determination of the midsagittal plane could be used in studies of symmetry in the human brain.

We validated the TP algorithm in infant brain MRI data in the following ways.

**Intra- and interrater reliability in neonatal and infant MRI data.** The results of the validation analysis using STAPLE in the neonatal data showed excellent sensitivity and specificity (always >95%), and hence excellent reproducibility and precision. The intra- and interrater reliability are shown in Tables 1 and 2 for the neonatal MRI data. The sensitivity of both intra- and interrater reliability for all parcels was >95% for both experts. The corresponding values of specificity were >99.9% for both intra- and interrater reliability. Similarly, the sensitivity for the intra- and interrater reliability was >95% and the specificity again >99.9% for the data obtained in 1-year-old infants (data not shown). These results demonstrate that highly precise and reliable results can be obtained independently from 2 expert users. In addition, they demonstrate that this technique is equally as reliable in larger, more mature brains as in the neonatal brain MRI data for which it was originally designed.

**Assessment of the effect of reformatting of original data.** The Mann-Whitney test was used to compare volumes of different parcels of the reformatted rotated image data to the original data in its initial position. Mann-Whitney represents a nonparametric test used to compare 2 independent groups of sampled data. This analysis demonstrated differences between parcel volumes obtained from original and rotated data, differences that are increasingly statistically significant for each increase in the angle of rotation needed to realign the data within the Talairach space. In fact, statistically significant differences were found in 8 of 16 parcel volumes with just a 2-degree angle of rotation along each axis (Table 3). These results demonstrate the importance of a parcellation algorithm that uses MRI data obtained in the original position without realignment and interpolation of the data.

**Discussion**

In this article, we describe our method for Talairach-based parcellation developed especially for neonatal brain MRI analysis. This method consists of a pipeline that includes registration of multichannel 3D MRI data, segmentation, and parcellation. The parcellation procedure is performed without any resampling of the original SPGR scans and employs a user-friendly interface designed to enhance identification of these often tiny landmarks in the newborn brain. Thus, parcellation is easily achieved using this interactive interface and an efficient algorithm, allowing rapid analysis of multiple cases.

Second, we demonstrate the precision and reliability of our TP approach by comparing intra- and interrater reliability. The sensitivity of >95% and specificity of >99.9% obtained for analyses in neonatal and infant data show high precision and reliability of this approach when used by the same or different users. The observation that sensitivity and specificity results obtained in 1-year-old infant data were also very high further demonstrates the potential utility of this algorithm for data obtained from older children and adults.

Recent medical studies have shown that there is considerable interest in quantification of different regions of the human brain. Therefore, in addition to volumetric
measurement of gyri through automatic parcellation of the cerebral cortex,4 computational methods were developed for parcellating frontal cortex,30 temporal lobe,31 and cerebral white matter,32 and for anatomical labeling of functional activation.33 However, the coplanar stereotactic atlas of the human brain using anatomical landmarks5 continues to be the most popular of the parcellation schemes. This is partly because the Talairach-based approach can be applied to the whole brain, and because it provides a straightforward approach for comparing brain measurements from different subjects or time points by using the same anatomic landmarks to denote the planes dividing the parcels.

Our Talairach-based parcellation approach was designed specifically for analysis of neonatal brain MRI data, as such data differ from the brain MRI data obtained in older subjects in a number of important ways. To date, all available tools for TP have been designed for adult neurological studies. Therefore, some pediatric studies used manual measures to revise the original Talairach grid to increase its applicability to the brains of older children.13,14 Obviously, manual adjustment of the planes of the Talairach grid necessitates significant processing time by the expert users, and likely introduces human error. For older children, such errors might be limited due to the relative maturity of their brain structures and the similar
Intrarater Reliability of Talairach-Based Parcellation on Newborn Brain MRI Data (4 cases analyzed 5 times)

<table>
<thead>
<tr>
<th>Talairach-Parcel</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expert 1 Mean ± SD</td>
<td>Expert 2 Mean ± SD</td>
</tr>
<tr>
<td>DLPF-right</td>
<td>96.017 ± 3.724</td>
<td>96.084 ± 3.730</td>
</tr>
<tr>
<td>DLPF-left</td>
<td>95.626 ± 3.290</td>
<td>95.611 ± 3.298</td>
</tr>
<tr>
<td>PM-right</td>
<td>96.303 ± 3.348</td>
<td>96.287 ± 3.364</td>
</tr>
<tr>
<td>PM-left</td>
<td>95.862 ± 3.324</td>
<td>95.622 ± 3.123</td>
</tr>
<tr>
<td>SM-right</td>
<td>96.123 ± 3.690</td>
<td>96.132 ± 3.683</td>
</tr>
<tr>
<td>SM-left</td>
<td>95.947 ± 3.920</td>
<td>95.972 ± 3.925</td>
</tr>
<tr>
<td>PO-right</td>
<td>95.060 ± 3.513</td>
<td>95.050 ± 3.511</td>
</tr>
<tr>
<td>PO-left</td>
<td>95.309 ± 3.369</td>
<td>95.315 ± 3.368</td>
</tr>
<tr>
<td>IO-right</td>
<td>95.793 ± 3.111</td>
<td>97.172 ± 2.847</td>
</tr>
<tr>
<td>IO-left</td>
<td>96.163 ± 3.076</td>
<td>96.140 ± 3.075</td>
</tr>
<tr>
<td>MT-right</td>
<td>95.676 ± 2.586</td>
<td>95.667 ± 2.589</td>
</tr>
<tr>
<td>MT-left</td>
<td>96.358 ± 2.137</td>
<td>96.401 ± 2.136</td>
</tr>
<tr>
<td>SG-right</td>
<td>97.523 ± 1.270</td>
<td>97.550 ± 1.269</td>
</tr>
<tr>
<td>SG-left</td>
<td>97.610 ± 1.120</td>
<td>97.605 ± 1.119</td>
</tr>
<tr>
<td>OF-right</td>
<td>97.386 ± 1.841</td>
<td>97.391 ± 1.850</td>
</tr>
<tr>
<td>OF-left</td>
<td>97.234 ± 1.689</td>
<td>97.235 ± 1.696</td>
</tr>
</tbody>
</table>

DLPF = Dorsolateral prefrontal, PM = premotor, SM = sensorimotor, PO = parieto-occipital, IO = inferior-occipital, MT = midtemporal, SG = subgenual, OF = orbitofrontal.

Table 2. Interrater Reliability in Newborn Brain MRI Data (4 cases analyzed 5 times)

<table>
<thead>
<tr>
<th>Talairach-Parcel</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean ± SD</td>
<td>Mean ± SD</td>
</tr>
<tr>
<td>DLPF-right</td>
<td>95.833 ± 3.687</td>
<td>99.997 ± 0.0036</td>
</tr>
<tr>
<td>DLPF-left</td>
<td>95.394 ± 3.248</td>
<td>99.997 ± 0.0041</td>
</tr>
<tr>
<td>PM-right</td>
<td>96.222 ± 3.402</td>
<td>99.996 ± 0.0067</td>
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<tr>
<td>PM-left</td>
<td>95.628 ± 3.280</td>
<td>99.996 ± 0.0064</td>
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<tr>
<td>SM-right</td>
<td>96.006 ± 3.636</td>
<td>99.996 ± 0.0045</td>
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<tr>
<td>SM-left</td>
<td>95.827 ± 3.875</td>
<td>99.996 ± 0.0047</td>
</tr>
<tr>
<td>PO-right</td>
<td>95.101 ± 3.415</td>
<td>99.998 ± 0.0022</td>
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<td>PO-left</td>
<td>95.198 ± 3.318</td>
<td>99.998 ± 0.0025</td>
</tr>
<tr>
<td>IO-right</td>
<td>96.339 ± 2.995</td>
<td>99.974 ± 0.065</td>
</tr>
<tr>
<td>IO-left</td>
<td>96.042 ± 3.041</td>
<td>99.994 ± 0.0079</td>
</tr>
<tr>
<td>MT-right</td>
<td>95.592 ± 2.530</td>
<td>99.997 ± 0.0043</td>
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<td>MT-left</td>
<td>96.245 ± 2.096</td>
<td>99.997 ± 0.0029</td>
</tr>
<tr>
<td>SG-right</td>
<td>97.023 ± 1.254</td>
<td>99.992 ± 0.0108</td>
</tr>
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<td>SG-left</td>
<td>97.458 ± 1.066</td>
<td>99.991 ± 0.0124</td>
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<tr>
<td>OF-right</td>
<td>97.249 ± 1.828</td>
<td>99.990 ± 0.0126</td>
</tr>
<tr>
<td>OF-left</td>
<td>97.016 ± 1.687</td>
<td>99.993 ± 0.0102</td>
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</tbody>
</table>

DLPF = Dorsolateral prefrontal, PM = premotor, SM = sensorimotor, PO = parieto-occipital, IO = inferior-occipital, MT = midtemporal, SG = subgenual, OF = orbitofrontal.

imaging properties to those of adults. In contrast, fitting the neonatal brain into a Talairach grid of the average adult brain is almost impossible because of the much smaller size and immature gyral pattern of the neonatal brain. Thus, the accuracy of such an approach in the newborn brain would probably be quite poor.

In addition, TP has generally been accomplished by aligning the MRI data into the Talairach or ideal space. This procedure requires reformatting of the original grayscale images, which are invariably of lesser quality compared with the original data. In neonatal MRI, it is critical to preserve data in the original position, as shown by our analysis of the effect of rotation and reformatting of the data. This effect of reformatting is likely due to the lack of signal contrast in neonatal brain MRI and the small size of landmarks such as the AC and PC, which would therefore be significantly affected by rotation and interpolation of the data.

To our knowledge, the presented approach is the first TP method that has been developed and validated for use in neonatal brain MRI data. Our validation studies show our approach to be highly precise in the neonatal brain when used by experts familiar with neonatal brain anatomy. This TP algorithm will likely also prove valuable for analyzing brain MRI data from fetuses, older children, and adults.

### Appendix

Sensitivity and specificity are determined by the Simultaneous Truth and Performance Level Estimation (STAPLE) as follows:

\[
p_j = \frac{\sum_{i:D_j=1} W_i}{\sum_{i:D_j=0} W_i + \sum_{i:D_j=1} W_i}
\]
### Table 3. The P Values Obtained Using the Mann-Whitney Test to Compare Volumes of Each Parcell of the Rotated Reformatted Data When Compared With the Original Data

<table>
<thead>
<tr>
<th>Talairach-Parcell</th>
<th>Initial Position</th>
<th>1 Deg</th>
<th>2 Deg</th>
<th>3 Deg</th>
<th>4 Deg</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Mean ± SD</td>
<td>Mean ± SD</td>
<td>P</td>
<td>Mean ± SD</td>
<td>P</td>
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<tr>
<td></td>
<td>DLPF-right</td>
<td>21.2 ± 1.30</td>
<td>19.8 ± 1.48</td>
<td>.19</td>
<td>19.2 ± 1.30</td>
</tr>
<tr>
<td></td>
<td>DLPF-left</td>
<td>25.4 ± 1.14</td>
<td>22.3 ± 1.20</td>
<td>.02</td>
<td>20.4 ± 1.14</td>
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<tr>
<td></td>
<td>PM-right</td>
<td>11.4 ± 1.14</td>
<td>12.8 ± 1.64</td>
<td>.11</td>
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<tr>
<td></td>
<td>PM-left</td>
<td>15.2 ± 0.84</td>
<td>16.6 ± 1.14</td>
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<td>17.8 ± 0.84</td>
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<tr>
<td></td>
<td>SM-right</td>
<td>41.0 ± 1.58</td>
<td>43.8 ± 1.10</td>
<td>.02</td>
<td>43.6 ± 2.07</td>
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<td></td>
<td>SM-left</td>
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<td>47.4 ± 1.14</td>
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<td>38.0 ± 0.71</td>
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<td>PO-right</td>
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<td>.98</td>
<td>14.4 ± 1.14</td>
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<td>PO-left</td>
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<td>21.4 ± 2.07</td>
<td>.87</td>
<td>18.0 ± 1.00</td>
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<tr>
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<td>IO-right</td>
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<td>70.6 ± 2.07</td>
<td>73.6 ± 2.97</td>
<td>.10</td>
<td>76.4 ± 2.07</td>
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<td></td>
<td>MT-right</td>
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<td>28.4 ± 1.14</td>
<td>.02</td>
<td>24.0 ± 1.58</td>
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<td></td>
<td>MT-left</td>
<td>35.0 ± 1.58</td>
<td>29.8 ± 1.48</td>
<td>.04</td>
<td>21.4 ± 2.18</td>
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<td>SG-right</td>
<td>137.4 ± 2.07</td>
<td>144.0 ± 3.94</td>
<td>.00</td>
<td>133.0 ± 2.92</td>
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<td></td>
<td>SG-left</td>
<td>104.0 ± 4.85</td>
<td>101.8 ± 4.92</td>
<td>.41</td>
<td>106.6 ± 5.18</td>
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<td></td>
<td>OF-right</td>
<td>63.0 ± 5.61</td>
<td>62.2 ± 5.45</td>
<td>.79</td>
<td>67.4 ± 1.95</td>
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<td>OF-left</td>
<td>44.2 ± 4.32</td>
<td>42.2 ± 5.36</td>
<td>.88</td>
<td>45.8 ± 3.90</td>
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References


