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Improved explanation of human intelligence using cortical features with second order moments and regression

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ABSTRACT

Background: Cortical features derived from magnetic resonance imaging (MRI) provide important information to account for human intelligence. Cortical thickness, surface area, sulcal depth, and mean curvature were considered to explain human intelligence. One region of interest (ROI) of a cortical structure consisting of thousands of vertices contained thousands of measurements, and typically, one mean value (first order moment), was used to represent a chosen ROI, which led to a potentially significant loss of information.

Methods: We proposed a technological improvement to account for human intelligence in which a second moment (variance) in addition to the mean value was adopted to represent a chosen ROI, so that the loss of information would be less severe. Two computed moments for the chosen ROIs were analyzed with partial least squares regression (PLSR). Cortical features for 78 adults were measured and analyzed in conjunction with the full-scale intelligence quotient (FSIQ).

Results: Our results showed that 45% of the variance of the FSIQ could be explained using the combination of four cortical features using two moments per chosen ROI. Our results showed improvement over using a mean value for each ROI, which explained 37% of the variance of FSIQ using the same set of cortical measurements.

Discussion: Our results suggest that using additional second order moments is potentially better than using mean values of chosen ROIs for regression analysis to account for human intelligence.

1. Introduction

Intelligence is commonly measured using standardized tests such as Wechsler Adult Intelligence Scale Revised (WAIS) and Multidimensional Aptitude Battery (MAB) tests [1,2]. FSIQ scores typically are obtained from the subtests of WAIS. In this study, we extracted FSIQ scores from eleven subtests of the Korean version of WAIS test. There are many metrics shown to be correlated to human intelligence. Size of the brain, volume of the gray and white matters, and cortical thickness were shown to be well correlated with human intelligence [3–5]. Researchers investigated intelligence using simple global measures (i.e., size of the brain) and local cortical measures (i.e., cortical thickness) requiring accurate neuroimaging techniques. Some adopted method of correlated vectors with functional MRI and others adopted studies of lesion patients find neuroanatomical correlates of human intelligence [6,7]. Recent advances in neuroimaging have enabled researchers to explore how brain structures and functions are related to measures of human intelligence [8]. Many studies have adopted structural MRI to find neuroanatomical correlates of human intelligence [9]. The cerebral cortex could be characterized by various features defined on the cortical surface. The cortical thickness has been widely adopted to find neuroanatomical correlates of intelligence among many cortical features [5]. Some found neuroanatomical correlates of intelligence in the prefrontal and temporal regions based on cortical thickness [5]. Others reported that subjects with higher intelligence quotient (IQ) tend to have a thicker cortex in the frontal region than subjects with lower IQ [10]. Other cortical features, including sulcal depth, surface area, and mean curvature, were also used to find neuroanatomical correlates of human intelligence [11,12]. In our previous

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study, the cortical thickness, sulcal depth, mean curvature, and surface area were used to explain FSIQ for 78 subjects [13].

Cortical features are defined over the whole cortical surface, which consists of tens of thousands of vertices. Researchers are mainly interested in how different brain regions and the associated cortical features are differentially affecting FSIQ. Many existing studies specified brain regions using ROIs transferred from a pre-computed atlas template. We adopted the same approach where the ROIs were derived from the well-received automated anatomical labeling (AAL) atlas template [14]. Cortical features are assigned to different ROIs for further statistical analysis with FSIQ. A sample mean (i.e., taking one value) or all the measurements within a given ROI may be used for the analysis. Representing one ROI with just one value (i.e., sample mean) causes a significant loss of information, as one ROI may contain thousands of measurements. Using all the measurements within an ROI for the statistical analysis is undesirable, because cortical measurements of adjacent vertices are highly correlated. In this study, we explored ways to extract a few values from a given ROI so that an increased amount of information would be available for a given ROI. We believed that the FSIQ could be better explained in terms of explained variance with better information available. One ROI may be subdivided into many smaller ROIs related to different neuro-anatomical implications. The corpus callosum includes splenium and genu sub-ROIs, which serve different functions. With this analogy, it is worthwhile to pursue a few representative values per ROI rather than just one value. We adopted the second order moment (i.e., variance) for each ROI in addition to the first-order moment (i.e., sample mean). This approach is a middle-ground between the two extremes of using one value to represent an ROI and using thousands of values.

The moment values of the chosen ROIs need to be analyzed with FSIQ. Analysis using standard multiple linear regression is feasible, but better-performing alternatives are available. Partial least squares regression (PLSR) predicts a set of dependent variables (FSIQ) from a set of independent variables (i.e., cortical measurements) that maximizes the covariance between the independent and dependent variables, and has been well received recently [15]. We are interested in finding a combination of cortical measurements that best predicts FSIQ in terms of variance explained, so PLSR was adopted.

The main goal of this study is (1) to propose a technological improvement to extract more meaningful information from ROI measurements using second order moments, and (2) to show the improvements of the new approach compared to using mean values for chosen ROIs to account for the explained variance of FSIQ. Our goal is not to associate certain areas of the brain with cognitive capabilities, but to propose a technological improvement to better account for human intelligence with cortical features. Second order moments are used to extract non-correlated measurements from ROIs in addition to the simple mean values. This method is used to analyze existing data to better explain the variance of FSIQ using various cortical features [13]. The combination of (1) using four cortical features to account for human intelligence, and (2) using additional second order moments besides simple mean values of cortical measurements to represent an ROI could not be found in existing literature to the best of our knowledge.

2. Methods

2.1. Data collection

Our data of 78 subjects came from the previous study where 164 subjects were considered [9]. Below describes the procedure for data collection taken from the previous study. Protocols were approved by the relevant institutional review boards (Seoul National University, Catholic University, Gachon University of Korea), and written informed consent was obtained from participants. 469 volunteers were recruited through advertisements and screened to cover the entire range of intelligence except the potentially retarded range. They tried to obtain an equal representation of subjects in all ranges such as average, high, and superior IQ by recruiting more subjects with superior IQ. 225 healthy volunteers were retained with a wide distribution of WAIS FSIQ and 164 of them received anatomical MRI imaging at Gachon University, Korea. The previous study contained subjects in all ranges of IQ such as average, high, and superior IQ category in equal representation. In this study, we chose 78 subjects out of 164 to cover a wide distribution of WAIS full-scale IQs ($81 < \mathrm{IQ} < 150$). Subjects aged between 17 and 27 were chosen to avoid developmental or aging periods when the brain changes radically [10]. All participants underwent the Korean version of the WAIS revised test. The WAIS is a standard IQ test that incorporates 11 subtests on diverse cognitive abilities: Information, Comprehension, Vocabulary, Similarities, Block Design, Object Assembly, Picture Completion, Digit Span, Arithmetic, Digit Symbol, and Picture Arrangement [16]. Details regarding subject, IQ data, and potential correlation among subjects are found in Table 1. For MRI Images, contiguous 0.9 mm axial 3D T1 weighted Magnetization Prepared Rapid Gradient Echo (MPRAGE) images were acquired with a 1.5T MR scanner (Siemens) with the following parameters: TR = 1160 ms, TE = 4.3 ms, flip angle = 15°. The field of view (FOV) was 224 mm, and matrix size was 512×512 and the number of slices was192 (the x, y, z dimensions of the reconstructed voxel: $0.44 \times 0.44 \times 0.90\ \mathrm{mm}^3$).

2.2. Image pre-processing

MRI images were spatially registered to a standard space in an affine fashion and then corrected for non-uniformities in intensity. The registered and corrected images were then classified into white and gray matter, cerebrospinal fluid, and background using a neural-net classifier [17]. The Constrained Laplacian-based Automated Segmentation with Proximities (CLASP) algorithm was used to extract the cortical surface [18]. A surface model for each brain hemisphere was constructed using 81,924 high-resolution polygonal 3D meshes. We applied a 2D surface based non-rigid registration algorithm based on a geodesic distance from the gyral crown vertex [19]. Simply put, the registration encourages matching of gyral patterns with appropriate smoothing. The registration algorithm adopted an optimization approach of coarse-to-fine manner using triangle meshes. At the coarse level, 1280 faces of triangle meshes were used. At the fine level, 81,924 faces were optimized. We chose the MNI space as the common space to compare different MRI images. The registration software established spatial correspondence between a given image and a predefined template image, and all 78 images were registered onto a common template so that they could all be compared on a

Table 1
Demographic and IQ data. Values are reported using mean and standard deviation (SD). SD values are reported in the parenthesis. *P*-values were computed from two sample *t*-tests.

	Total ($n=78$)	Male ($n=39$)	Female ($n=39$)	*p*-value
Age	22.7 (1.9)	22.6 (2.2)	22.9 (1.6)	0.51
Full scale IQ	120.8 (13.0)	122.6 (13.0)	119.0 (12.9)	0.22
Verbal IQ	120.2 (13.8)	122.2 (14.0)	118.1 (13.6)	0.19
Performance IQ	117.2 (12.1)	118.3 (12.0)	116.1 (12.2)	0.41