Detecting Outliers in fMRI studies with Small Sample Size

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Introduction

The purpose of this study was to develop a method to detect outliers for smaller subject populations. In most of the fMRI experiments conducted, one assumes that the variations among subjects are minimal and that the resulting errors are random and Gaussian in nature. However, the data sets used in fMRI are small (usually less than 20 subjects) and cannot be easily determined as fitting the Gaussian model. Besides, increasing the risk of errors in the measurement of the distribution parameters, there is a possibility that the distribution which is being modeled is not the correct distribution. In the case of an outlier, there is no immediate way to differentiate between outliers and normal data points. The outliers can either increase or decrease the "mean" averages. To compensate for this, the subject population usually associated with the fMRI experiments (15-20 subjects) can be increased (80 or more subjects) to make it easier to detect outliers and give a more accurate resampling data sets. In addition to being expensive due to increased scanning time, and other subject related costs, for certain patient populations, it is not possible to increase the sample size to 80 or 100. In this paper, we present a method for detecting outliers in small sample sizes.

Theory

BOOTLIER is a resampling based outlier detection method that has recently been developed by Minge and Singh [1]. In order to make the distribution distinctly multimodal, more weightage is paid to the extreme values. In the BOOTLIER method this is accomplished by subtracting the "trimmed mean" from the "mean". A 5% resampled data trimming was done to the resampled data and this trimmed mean was subtracted from the total mean to maximize the effect of any outliers. The resampling was typically done a large number of times (10000). If the resampled data did not contain any outliers, there would be minimal difference between the "mean" and the "trimmed mean". In the case of the resampled data containing any outliers, there would be a difference between the "mean" and "trimmed mean". The "mean" would be a higher (or lower) based on the outlier value. The "trimmed mean", however, will not change and it will be similar to the mean with the absence of the outliers. As a consequence, the resampled distribution will have a significant difference compared to the resampled data sets that have no outliers. Thus, the data distribution obtained after using the bootstrap with trimmed mean will be more sensitive to the presence of any outliers.

Method

All the data sets were collected using a 3T Siemens Allegra system. For each subject, echo-planar images were obtained in the axial plane in six slices covering the motor cortex using the following parameters: 64×64 matrix, TR/TE=1000/27 ms, FOV=22 cm, and slice thickness=5 mm. Twelve subjects participated in the experiment (Three male, Nine female). The mean age for the subjects was 22 years. Each of the subjects performed a bilateral finger-tapping task paradigm. Each paradigm lasted for 139 seconds (2 minutes 19 seconds) and was scanned at least three times. The length of each paradigm for all the subjects was kept the same.

Results and Discussion

To determine the variability between the different scans for each subject, the number of voxels that passed the threshold as a function of threshold parameter was obtained. Activated voxels, as a percentage of the total brain volume, were calculated. A graph was created for each subject, which showed how consistent each individual scan was. Most of the subjects showed a significant reproducibility during bilateral finger-tapping experiments. Although in two subjects, there were substantial differences in the scans. For one subject, the last scan series varied significantly compared from the other scans. Head motion may have been severe enough for this scan, that the motion-correction applied to the series was not entirely effective in reversing this.

Although deviations from the mean values were found, when the Gaussian method was applied it was difficult to determine how many subjects were outliers. The Gaussian distribution may not have worked due to the fact that there were too few time points or that the distribution in itself was not Gaussian. Therefore, BOOTLIER was used to correct any differences in the distribution. BOOTLIER resampling was performed on all the data sets to determine the number of outliers. After resampling the data sets 10,000 times, with six points removed from both ends of the distribution, two outliers were found within the distribution. These results were consistent with the fact that there were only two subjects whose scans varied from one another. Figure 1 A, shows a resampled bootstrap mean value of the percent of brain volume that was activated for all the subjects. It was not obvious if any outliers were present in the data sets. Figure 1B shows the distribution after BOOTLIER resampling. As can be seen distinct distributions were seen suggesting the presence of outliers in the data.

In this paper, a reliable method for detecting outliers using BOOTLIER statistical method was presented. Based on the data from the study, BOOTLIER was found to be effective in detecting outliers from small data sets for each of the conditions. Using a number of different distributions, the BOOTLIER methods consistently detected outliers.

References

[1]. Singh K, Minge X. Bootlier plot-Bootstrap based outlier detection plot. *Sankhya A* **65** (3), 2003, 532-559

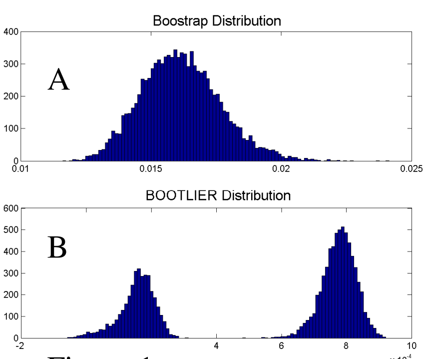

Figure 1