

Robert W Cox
National Institute of Mental Health, Bethesda MD USA

A method is proposed for indication of "unusual" images and data values in a time series of MR images. The primary purpose of this method is to draw the investigator's attention to potential problems with the data. It is sensitive to signal changes caused by sudden movements, scanner hardware problems, and glitches in the reconstruction software.

Introduction

About 1 gigabyte of image data is gathered in a typical 2 hour FMRI scanning session. Many things can go wrong with the image acquisition process. The steps below are not intended to fix problems, but rather to alert the investigator to "unusual" values in the time series.

The method uses median and MAD statistics instead of mean and standard deviation. This choice makes it impossible for a few large values to influence the process strongly. Otherwise the basic idea is simple: compute the range of "usual" values, then mark and count "unusual" voxels.

Steps

1. The median value $m(\mathbf{x})$ is computed for each voxel \mathbf{x} : $m(\mathbf{x}) = \text{median}_{\{v(\mathbf{x}, t)\}}$, where $v(\mathbf{x}, t)$ is the voxel value at location \mathbf{x} and time t .
2. The clip-level $c > 0$ is determined by solving the equation $c = 0.5 \cdot \text{median}_{\mathbf{x}} \{m(\mathbf{x}) : m > c\}$. Voxels with $m > c$ are presumed to be outside the brain and are ignored in the following steps. (If using a local RF coil, this step should be skipped.)
3. For each voxel, the median absolute deviation is computed: $\text{MAD}(\mathbf{x}) = \text{median}_t \{|v(\mathbf{x}, t) - m(\mathbf{x})|\}$.
4. Values $v(\mathbf{x}, t)$ outside the interval $[m(\mathbf{x}) - a^* \text{MAD}(\mathbf{x}), m(\mathbf{x}) + a^* \text{MAD}(\mathbf{x})]$ are taken to be outliers, where $a = Q^{-1}(p/N)^*(\pi/2)^{1/2}$, $Q(\cdot)$ is the reversed Gaussian cdf, N is the length of the time series, and p is a nominal probability threshold (default value $p=0.01$). [If $v(\mathbf{x}, t)$ is Gaussian white noise, then the probability that any individual value is outside the above range is approximately $p/(2N)$.]
5. For each time t , the number of outlying voxels $n(t)$ is counted.
6. The median (n_{med}) and MAD (n_{MAD}) of $n(t)$ are calculated. Any time t with $n(t) > n_{\text{med}} + 3.5 \cdot n_{\text{MAD}}$ is flagged as having an unusual number of outliers. These images should be examined by the investigator.

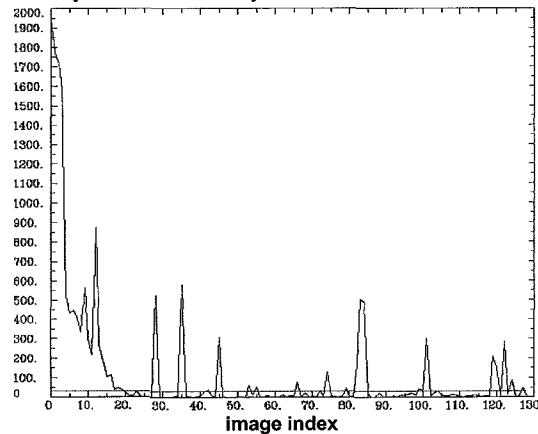
7. For each point (\mathbf{x}, t) , its "outlier-ness" $w(\mathbf{x}, t)$ is computed as

$$w(\mathbf{x}, t) = -\log_{10} Q\left(\frac{|v(\mathbf{x}, t) - m(\mathbf{x})|}{\text{MAD}(\mathbf{x})\sqrt{\pi/2}}\right), \text{ which}$$

measures how likely its variation from the median is, under the Gaussian distribution model. Voxels with large w should be examined by the investigator.

Example:

The graph below shows the outlier count $n(t)$ vs. t for a sample dataset. The horizontal line near the bottom is $n_{\text{med}} + 3.5 \cdot n_{\text{MAD}}$. The large counts at the start are due to the extra-bright images that occur prior to equilibration of longitudinal magnetization. The occasional spikes in the outlier count at later times are disturbing. Upon investigation, they were found to be due to intermittent problems with the RF amplifier, causing some slices to be about 5% under-bright. This outlier counting process led directly to this discovery.



This outlier detection process is also sensitive to sudden head movements, which cause voxels near the edge of the brain to suddenly increase or decrease substantially in brightness.

Software

Software for this calculation is included in the AFNI package, which is freely available at <http://afni.nimh.nih.gov/afni>. All datasets assembled with the AFNI software are now passed through this algorithm, which only takes about 10 seconds for a typical 35 megabyte imaging run (750 MHz AMD Athlon CPU).