Evaluation of outliers in acquired brain MR images

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Abstract. Pre-processing is an important stage in the analysis of magnetic resonance images (MRI), because the effect of specific image artefacts, such as intensity inhomogeneity, noise and low contrast can adversely affect the quantitative image analysis. The image histogram is a useful tool in the analysis of MR images given that it allows a close relationship with important image features such as contrast and noise. The noise and variable contrast are elements that locally modify the quality of images. The key issue of this study derives from the fact that the spatial histogram can contain outliers indicating corrupted image information through the disorder of the bins. These aberrant errors should be excluded from the studied data sets. Here, the outliers are evaluated by using rigorous methods based on the probability theory and Chauvenet (CC), Grubbs (GC) and Peirce's (PC) criteria. In order to check the quality of the MR images, the Minkowsky (MD), Euclidean (ED) and cosine (CD) distance functions were used. They act as similarity scores between the histogram of the acquired MRI and the processed image. This analysis is necessary because, sometimes, the distance function exceeds the co-domain because of the outliers. In this paper, 32 MRIs are tested and the outliers are removed so that the distance functions generate uncorrupted and real values.

1. Introduction
Magnetic Resonance Image (MRI) that is widely used in research as well as in clinical practice [1], texture analysis or segmentation images [2-3].

The outliers detection techniques used in the image processing domain include: satellite imagery, hyperspectral images, digit recognition, spectroscopy, mammographic image, and video surveillance [4]. The sources of these outliers are motion, changes in an image during the acquisition process, or regions which appear abnormal on the static image. The main goal of the current research is that of restoring and enhancing the structural neuro-MR images by outliers removing operation in order to make accessible subtle details of tissues that are usually highlighted with tiresome intensity windowing methods. In a broad sense, outliers are patterns that deviate from expected normal behaviour. The high accuracy analysis of neuro-MR images is often hampered and various correction methods were developed. Commonly, they are categorized into low pass filtering, statistical modelling
or surface fitting, or methods focused on mathematical modelling [5]. The statistical analysis of
the outliers is a way of improving the quality of a corrupted image.

Generally, the MR images are analysed in four or five stages, as follows: a) the first stage deals
with the image acquisition; b) in the pre-processing stage, various filters are used in order to eliminate
the noise or the artefacts acquired in the first stage; c) then the segmentation of the images (supervised,
unsupervised) could be accomplished [6]; d) structural approaches when the texture is represented by
well-defined primitives (microtexture); or e) hierarchy spatial arrangements (macrotexture) could
follow [2]. If the first two stages are compulsory for every image analysis, the choice of the last three
stages depends on the research goal.

Practically, what this study aims at is including a new processing stage between the acquisition and
the pre-processing stages. This is called detection of outliers (DO). Outliers can occur in any
histogram image distribution. In a histogram image, the outliers occur because a bin is distant from
other bins or the bins follow a sample kurtosis. In order to determine the outliers’ percentage from an
image the following tests were used: Chauvenet’s criterion (CC) [7], Grubbs’ criterion (GC) [8] and
Peirce’s criterion (PC) [9]. Chauvenet’s criterion is based on the idea of finding a probability band,
centred on the means of the normal distribution [7]. Peirce’s method is a more general approach and it
is applied in the case of more suspicious data values. The PC estimates the maximum allowable
deviation of a measured value from the data means to the standard deviation. Grubbs’ test is known as
the maximum normed residual test and it is based on normal distribution.

In order to check for the quality of the restored image after outliers correction, the following
distance-based methods were chosen: the Minkowsky (MD) [10], the Euclidean (ED) [10] and cosine
(CD) distances [11]. All these functions measure the difference between the original image histogram
and the histogram image corrupted by noise or by a modified contrast.

2. Materials and methods
The current study focuses on outliers detection tests and distance-based methods as tools for the
qualitative restoration of the neuro-MR images [12]. In order to identify the outliers from the image
histograms the following criteria were chosen.

1. Chauvenet's criterion is widely used in astronomy, nuclear technology, epidemiology, molecular
biology and in many fields of Physical sciences. It makes an arbitrary assumption regarding the data
rejection, namely all the data which lie within a “maximum deviation range” are assumed to be
probable [7].

2. Peirce's criterion is a better alternative to Chauvenet's criterion, because it does not make any
arbitrary assumptions [9].

3. Grubbs’ criterion is a robust test for the detection of outliers for a normal distribution. Before
applying GC it is necessary to check if the data could be approximated by a normal distribution and
the data under examination are in ascending order [8].

4. Distance-based methods Texture analysis is a major step in texture classification and a sound
analysis uses descriptors such as smoothness, coarseness and regularity. The histogram is a tool used
to graphically interpret a digital image in tonal distribution. Three distance measures Euclidian [10]
Minkowski [10] and the cosine distance [11] were applied between the histograms of the original
neuro-MR image and the modified image by contrast and noise were used.

3. Experimental data
The neuro-MR images used in this study were retrieved from the Harvard Medical School database
(http://www.med.harvard.edu/AANLIB/home.html). The images belong to a healthy aging patient.

During the proposed DO stage, the percentage of the outliers is established in order to verify the
correctness of the subsequent measurements. This stage can be implemented between the acquisition
and pre-processing stages. The logical steps to follow in the current study are:

(i) The images are tested with CC, PC and GC and the percentage of the outlier in the histogram
image is computed.
(ii) For each image, the contrast has been varied from 0.1 to 0.9, with step of 0.1. The level 1 means the image itself. For all modified images, the CC, PC and GC were tested and the percentage of outliers was computed. The histograms of the original image and the images with 0.3 and 0.6 modified contrast level are shown in figure 1.

![Figure 1](image1)

Figure 1. The histograms of the original and contrast modified images.

(iii) The Gaussian noise with variance ranges from 0.01 to 0.09 (with a step of 0.01) was added. Then, the CC, PC and GC were tested once again.

(iv) The pixels identified as outliers by CC, PC and GC are removed from the dataset.

(v) The similarity between images is tested by computing the distance functions between the original and modified images. Figure 2.a shows the representative distance functions ED, MD and CD, for different levels of the contrast. Label 1 denotes the distance functions computed for the original image (with outliers) and label 2 is for images without outliers. Figure 2.b presents only the ED, MD and CD metrics for images with outliers and added noise, because a perfect overlapping with the metrics for images without outlier and added noise has been found.

![Figure 2](image2)

Figure 2. The distance functions for: (a) Contrast variation; (b) Noise variance

In the case of contrast level variation, the experimental data show that the CC, GP and PC gave different values of outlier percentage. The outlier percentage takes higher values for 0.2 and 0.3 contrast levels and lower values for levels of 0.8 and 0.9, in the case of CC. The percentage is constant for PC. In case of noise level variance, the outliers are not detectable by CC and PC (the last criterion detects outliers only for the noise levels of 0.08 and 0.09). The GC detects a relatively lower percentage of outliers.

**4. Discussions**

Nowadays, the challenge is to detect the outliers in neuro-MR images. An experimental study was conducted in order to compare the ability of Chauvenet's, Peirce’s and Grubbs’ criteria in outlier detection. Specifically, the contrast is increased in the range from 0.1 to 0.9 and Gaussian noise is added with variance ranging from 0.01 to 0.09. For each experimental image the percentage of outliers
is computed. The quality of restoration process is verified by using the distance metrics between images with and without outliers.

When referring back to outliers in image, noise raises a sensitive issue. Typically, noise in the data tends to be similar to the actual outliers and it becomes difficult to remove the outliers from images. The current study highlights the idea that noise is a feature which cannot influence the outlier percentage in neuro-MR images.

The data from Figure 2a show a linear relationship of the similarity distance functions for both analysed cases (with/without outliers). The behaviour of the outliers related to the contrast variation is arguable. Thus, if the contrast level increases the distance between histogram images decreases, and the outliers percentage decreases, too. The ED1 distance is higher that ED2 indicating a higher similarity between images when the outliers were removed. The expected results are also confirmed by MD1 and MD2. On the contrary, CD1 and CD2 are highly overlapping and this indicates that the cosine distance is insensitive to the outliers.

The perfect overlapping of the EDs, MDs, and CDs in the case of noisy images (see Figure 2.b) leads to the conclusion that the analysis of the noise into image as an outlier can hardly be said to be useful. In this case it is necessary that the nature of noise in a MR image is taken into account. Noise is not an error. Of course, noise is not a true signal but its values are closer to the true signal values.

The experimental results of the current study show that the DO stage is necessary in the neuro-MR images processing, because, in the first instance, the user must know if the images contain outliers, the percentage of these outliers and how much they can influence the experiment results.

Conclusions
This study has brought together various outlier detection techniques. Three criteria for the outliers percentage detection were studied and three distance-based methods were employed for the detection of the similarity between images when the outliers were removed. The MR acquisition process is prone to various artefacts that affect the image features as contrast or noise. In case of contrast variation, the distance functions allow the conclusion that the images are affected by outliers. On the other hand, noise is not an error and the outliers in noisy images cannot be identified. Therefore, the necessity of this new proposed stage “Detection of outlier (DO)” should be in-depth studied for further applicability in the analysis of the complex systems as neuro-MR images.

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