# Introduction

The work described here is the implementation of the algorithm described in [1] and [2].

The method consists in learning the parameters of a reference scale of intensities defined using a set of images as part of a training dataset. The reference distribution is defined as an average of a set of statistical parameters from the training datasets.

# Main Work

The code consists in several steps:

1. NIfTI image Downloading of 12 subjects.

As part of the downloading, a data structure called *imageData* is created which contains the 12 images, their respective NIfTI metadata information, their subject description and if they are part of the training dataset.

1. The landmarks, percentiles or other statistical orders, referenced through the code as ‘*peak’*, are defined in two functions setUpPercentiles and setUpPeaks. The landmarks are used in the standardization step if the image is part of the training set and for all the images in the transformation step.

The minimum and maximum, p1 and p2 minimum percentiles are computed. In addition, of m1, m2, p1 and p2; the authors recommend using at least one more landmark, *w*, the shoulder of the background hump when the histogram is unimodal and μ, the second mode of the histogram when it is bimodal.

The histogram-specific parameters landmarks of each image are manually determined (Table 1):

* Each image's histogram is plotted, highlighting the locations of m1, m2, p1, p2​, and additional user-selected landmarks. These landmarks are determined based on the height of the bins, which represent the total number of pixels at each intensity level in the image.
* The function findNthLargestBinsIntensity identifies the peak intensity values by analyzing the histogram. It selects the intensity corresponding to the nth largest bin, where bins are sorted by the number of pixels (bin counts).
* plotHistogramWithLandmarks plots a histogram with all its landmarks: m1, m2, p1, p2​, and other mode related landmarks (Fig. 1).

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Fig. 1: Subject 15 Histogram with its landmarks

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Subject | pc1 | pc2 | Mode1 (bin no) | Mode 2 (bin no) |
| 2 | 10 | 99.8 | 2 | 5 |
| 3 | 10 | 99.8 | 2 | 20 |
| 4 | 10 | 99.8 | 2 | 20 |
| 5 | 10 | 99.8 | 2 | 20 |
| 6 | 10 | 99.8 | 2 | 41 |
| 7 | 10 | 99.8 | 2 | 6 |
| 9 | 10 | 99.8 | 2 | 6 |
| 10 | 10 | 99.8 | 2 | 10 |
| 11 | 10 | 99.8 | 2 | 6 |
| 12 | 10 | 99.8 | 2 | 6 |
| 13 | 10 | 99.8 | 2 | 6 |
| 15 | 10 | 99.8 | 2 | 6 |

Table 1: Subjects with their major landmarks.

* Pc1 was set to 10% and not 0 because most of the largest peak in the histogram of the images correspond to the background pixels with 0 intensity.
* Other percentiles used are: 20% 30% 60% 70%.

1. S1 and S2 are computed, S1 is set to 1, s2 to the maximum of all the pixel intensities of the whole dataset of images (finds1s2).
2. The landmarks of each are standardized following the standardization algorithm (Fig. 2).

If the minimum of an image intensities is less than pc1 it is set to pc1 and similarly of the maximum of an image intensities is greater than pc2 it is set to pc2. Tuning of these minimums or maximums could be further refined in future iterations of the algorithm (functions: applyStandardizationToLandmarks, applyStandardizations and standardize).

1. A matrix is created which has for rows rhe landmarks of the images of the training datasets (all subjects but 13 and 15). The means of these landmarks are computed column-wise and stored in each image metadata structure. (Fig. 2)

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Fig. 2: Standardization Algorithm.

1. Each image is then transformed including subject 13 and 15 which were not part of the training datasets using the mean of the standardized landmarks (based on the training dataset images) following the transformation algorithm (Fig. 3). The algorithms of the transformed images are also computed and stored for further access (transformImages, transformImage).

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Fig. 3: Transformation algorithm.

# Evaluation

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Fig. 4: Subject MRI Image Histograms before and after Scale Standardization.

From the provided histograms, the following observations can be made regarding the image histograms **before** and **after transformation** (plotBothHistograms, Fig. 4):

**Before Transformation (Original Image Histograms):**

1. **High Intensity Concentration at Low Values**:
   * A significant proportion of the pixel intensities are concentrated at lower intensity values (between 0 and 200), as seen from the tall bar around these values.
   * This suggests that the original images have a limited range of pixel intensity values, with most pixels clustered in the lower intensity range.
2. **Sparse Distribution at Higher Intensities**:
   * The histogram shows a sparse distribution of pixel counts as intensity values increase beyond 200.
   * Very few pixels have intensities higher than 600, indicating that the images may have poor contrast or very low dynamic range in the higher intensity regions.

**After Transformation (Transformed Image Histograms):**

1. **More Even Distribution Across Intensity Range**:
   * The transformed image histogram shows a more even spread of pixel intensities, with fewer pixels concentrated at the lower intensity values compared to the original images.
   * There are a more gradual distribution of pixel counts across a wider intensity range, suggesting the transformation has redistributed the intensities more evenly across the scale.
2. **Improved Dynamic Range**:
   * The pixel intensities now span a larger portion of the intensity spectrum (from 0 to around 1000). This suggests that the transformation has improved the dynamic range of the images, enhancing the contrast.
3. **Peak Distribution Shift**:
   * The transformation has shifted the location of intensity peaks (previously concentrated at very low values) toward a more balanced intensity range.
   * This can indicate that the transformation algorithm has stretched the intensity values to make the image more interpretable and balanced.

**General Observations:**

* **Improved Contrast**: The transformation likely aimed at improving the image contrast by redistributing pixel intensities more evenly across the available range.
* **Normalization**: The transformation could also be a form of normalization, where the pixel intensities are scaled to a standard range, improving the visibility of features across different intensity levels.

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Fig. 5: Similar Brain MRI Slice cross subjects before transformation

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Fig. 6: Similar Brain MRI Slice cross subjects after Scale Standardization.

**Observations from the same slice across subjects before and after scale standardization (Fig. 5 and 6, plotSliceCrossSubjects):**

**Before Standardization (First Plot):**

1. **Variability in Contrast**:
   * There is significant variability in contrast between subjects. Some slices appear overexposed (too bright), such as those from Subject 2 and Subject 4, while others, like those from Subject 3 and Subject 9, display better contrast.
   * This variability can make cross-subject analysis difficult, as intensity values are not consistent across all images.
2. **Detail Visibility**:
   * For some subjects (e.g., Subject 6), structural details are less visible due to very high or low intensity levels, leading to saturation or darkened images.
   * The lack of consistent intensity scaling means that fine details, such as brain tissue structure, are difficult to compare across subjects.
3. **Inconsistent Dynamic Range**:
   * Different subjects exhibit varying intensity ranges. For example, the images from Subject 13 and Subject 12 are washed out, indicating an uneven dynamic range and possibly poor contrast settings in the original images.

**After Standardization (Second Plot):**

1. **Improved Contrast Consistency**:
   * After scale standardization, the contrast between subjects has improved. Most images have a similar brightness and contrast level, with clear structures visible in each slice (e.g., ventricles and brain tissue boundaries).
   * Subjects such as 2, 4, and 6, which previously showed overexposed regions, now exhibit better intensity distribution, making structural details more apparent.
2. **Enhanced Detail**:
   * The details in the brain anatomy are more uniformly visible across subjects. For example, previously washed-out slices from Subject 13 and Subject 12 now have clearer definitions of brain structures.
   * Darker images like Subject 12’s slice are also much better balanced after transformation, revealing more details that were previously obscured.
3. **Harmonized Dynamic Range**:
   * The intensity scaling has effectively harmonized the dynamic range across all subjects, allowing for a more meaningful comparison of structural features.
   * This suggests the transformation process successfully normalized the intensity values, allowing similar intensities across different subjects to be comparable in a more meaningful way.

**Reference**:

[1] Laszlo G, Nyul and Jayaram K. Udupa, “On Standardizing the MR Image Intensity Scale”, Magnetic Resonance in Medicine 42:1072-1081 (1999)

[2] Laszlo G, Nyul and Jayaram K. Udupa, “New Variants of a Method of MRI Scale Standardization”, IEE Transactions on Medical Imaging, VOL.19. N).2, Feb 2000.